Perspectives on productivity and business cycles in Europe

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Perspectives on Productivity and Business Cycles in Europe
Contributions of the Euro and the Lisbon Agenda to Growth

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Preface

Although this book has my name on the title page, many people have contributed to the research it contains. In the acknowledgements near the end of this study, I try give due credit to all my co-authors and collaborators, but I would like take the opportunity here to thank them all for the pleasant and productive interaction. More in general, the Faculty of Economics at the University of Groningen is a very collegial place with many colleagues willing to discuss research or just about any other topic. In addition, during the past years, I have enjoyed the hospitality of The Conference Board in New York and the National Institute of Economic and Social Research in London. Specifically, I would like to thank my supervisors, Bart and Jakob, who got me interested in a research career in the first place and who subsequently gave me all the space I could wish for to do the research I wanted to. In addition, many thanks go to Ward Romp, Marcel Timmer, Bob McGuckin, Jan Jacobs, Edwin Stuivenwold, Gerard Ypma and Mary O'Mahony for the good research and good times shared. Finally, I am also very grateful for the support of my family and friends, especially during the months where this dissertation actually had to be written. I promise I will not do it again.

Robert Inklaar

New York, November 2005

Chapter 1 Introduction

1.1 Europe's challenges

As the European Union (EU) struggles to maintain its political momentum in the face of growing popular resentment against further integration, its economic model is also challenged. Its two most important economic projects are the new common currency, the euro, and the Lisbon agenda to stimulate the competitiveness of European economies. However, both projects face headwinds. The long-run sustainability of the euro is by no means guaranteed, which is exemplified by the resistance of France and Germany to the Stability and Growth Pact, the fiscal pillar of the Economic and Monetary Union (EMU). In addition, European competitiveness has slipped to such an extent compared to resurgent growth in the United States that the European Commission (2004) speaks of Europe's 'structural productivity problem.'

In this study, I analyze a number of aspects of these two major policy projects. These analyses show that the challenges to these programs are related in various ways. The key policy prescription is that the flexibility of European economies should be enhanced, specifically by reducing regulatory burdens, stimulating (cross-border) movement of labour and freeing up trade in services. These measures will help in responding to economic shocks, whether these shocks are cyclical disturbances or technological opportunities. The United States represents an example, where both adverse local cyclical developments are absorbed without too much economic pain as well as new technologies successfully exploited.

The competitiveness of European economies, and specifically the rate of productivity growth, is important to ensure a high standard of living. In the short run, a higher income per capita can also be realized through a higher employment rate, but while the employment rate cannot increase indefinitely, no such limits are apparent for productivity. This issue is set to become more important in the upcoming decades as 'baby boomers' retire and working-age populations shrink in most European countries.

Strong productivity growth can ensure that pension systems remain solvent without a decline in living standards for current workers.

Much commentary currently focuses on the spectacular growth performance of India and China, with cheap manufactured goods from China and outsourced ICT services from India threatening parts of the European and American economies. However, the immediate impact should not be exaggerated. In terms of income and productivity levels these countries still lag Europe and the U.S. by decades, so the rise of China and India mostly stimulates a more efficient division of labour.[1] When confronted with cheap imports, the most sustainable strategy is to compete on quality and innovativeness because the closure of Europe's borders against those imports provides only temporary relief at best, or worse, slows down structural improvement even further. A more immediate challenge for Europe is the resurgence of U.S. productivity growth. Whereas the average productivity level of the European Union was at the same level as the U.S. around the mid-1990s, a new productivity gap has opened up since. The strong performance of the American economy over the past decade stands in stark contrast to the lower GDP growth rates and higher levels of inactivity in many European economies. This suggests that Europe's competitive and innovative capabilities are lacking.

Despite these grudges against Europe's economies, it should be stressed that the European integration process of the past half century has been a remarkable success. Although still incomplete (particularly in the area of services), the realization of an internal market has created one of the largest economic free trade areas in the world, providing an enormous potential for growth and productivity gains. The Lisbon agenda is essentially meant to realize this potential by focusing on economic reforms, more jobs and innovation.

The other main economic project is the adoption of a common currency by twelve European countries. An important reason for adopting the euro has been to support further economic integration and growth within the euro area. In addition it was meant to provide a framework for a more robust fiscal and monetary regime in an area that is so

[1] GDP per person engaged in China and India is between ten and twenty percent of levels seen in Europe and the U.S. Even at current growth rates, it will take until at least 2040 before productivity levels would be at similar levels.

strongly integrated. As such, it represents an experiment of a unique scale in modern times. Still it is by no means certain that this project will ultimately turn out to be a success. For example, while Germany was one of the most vocal advocates of adopting strict fiscal rules to complement the common monetary policy, it has been among the first countries to break those rules. Even if the euro delivers benefits by way of greater competitiveness, there is a risk that these gains are outweighed by the costs of a common monetary policy.[2] Upon joining the euro area, the member countries surrendered their monetary policy and thereby an instrument to dampen the effects of recessions. Unless recessions occur at the same time in all member countries, monetary policy will not be suitable for all countries.

This study analyzes the challenges Europe faces in these two economic projects and the implications for European competitiveness from a number of different perspectives.[3] The next section discusses the prospects for the euro and the effects of the heterogeneity of the euro area, setting the stage for Chapters 2 and 3. Their main goal is to determine whether the costs of the common currency may become unsustainable in the future. Section 1.3 presents recent productivity developments and introduces Chapters 4 and 5. These chapters evaluate the importance of new information and communication technologies (ICT) diffusion and of cyclical factors in explaining the productivity growth gap with the United States. Through the analysis of Europe's productivity problem, these chapters suggest ways in which the goals of the Lisbon agenda could be achieved. Finally, Section 1.4 sketches the agenda for reform based on the findings of this study as well as other research and brings the two topics together in an integral fashion.

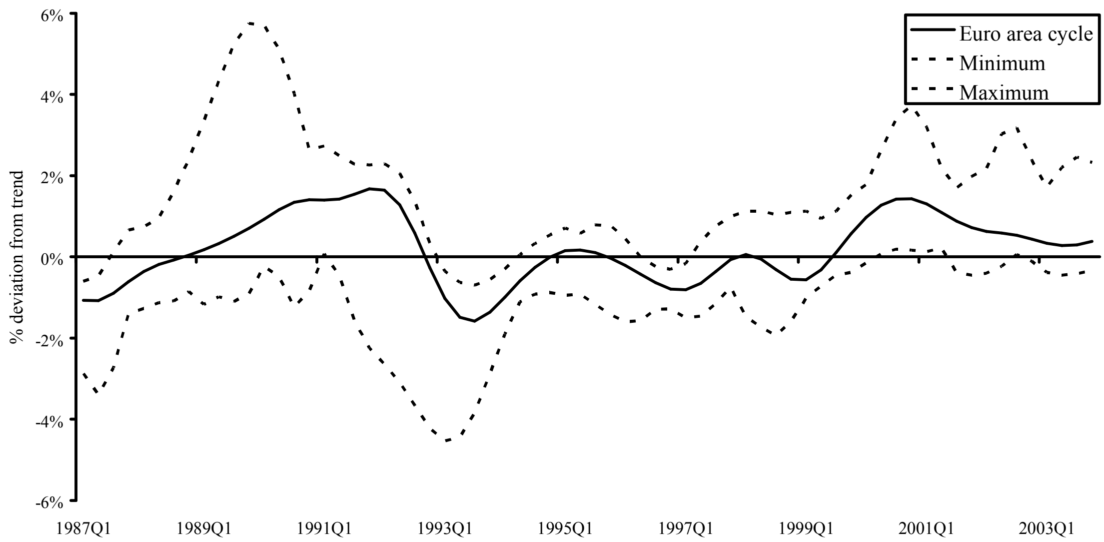
1.2 The costs of the euro and variations in business cycles

The most important consequence of the adoption of a common currency in the euro area is that monetary policy is the same for all member countries. In setting this policy, the European Central Bank (ECB) should only respond to economic developments in the area as a whole, but this may not be suitable for all countries in the monetary union. If

[2] Some would argue that the euro was introduced mainly for political reasons. Nevertheless, the costs of the euro may come to outweigh the combined economic and political benefits.
[3] This book deals exclusively with the 15 EU member states from before the accession of ten new member countries in May 2004. Europe and EU-15 will be used interchangeably.

business cycles vary substantially across countries within the euro area, monetary policy will be too accommodating for some countries, and too strict for others.[4] This issue is not just of academic interest as research by Nitsch (2004) has shown that inflation differences have led to the dissolution of currency unions in the past, and these inflation differences are (to a certain extent) related to differences in business cycles.

Figure 1.1 Euro area cycle and the range of cycles for euro area countries, 1987-2003



Source: OECD Quarterly National Accounts, supplemented with Eurostat and national data, see Table 1.1

Notes: Business cycle is estimated as the Baxter-King (1999) band pass filtered log of quarterly GDP of a synthetic euro area and each of the euro area countries, estimated over the period 1970-2003. Minimum is the smallest value for filtered GDP in any of the euro area countries in a specific quarter Maximum is the largest value for any of the countries.

Figure 1.1 illustrates this problem by showing output relative to trend for the euro area for the period 1987-2003.[5] As the figure shows, periods where output was above trend have alternated with periods of below-trend output. Periods where output is substantially below trend, such as in the early 1990s, are commonly referred to as recessions.[6] In addition to the euro area cycle, the highest and lowest output of the individual countries relative to their own trend is also shown. This makes clear that at

[4] Monetary policy can have a short-run effect on economic activity if there are frictions in the economy such as sticky prices (e.g. Calvo, 1983) or sticky information (e.g. Mankiw and Reis, 2002).

[5] The business cycle estimates are based on quarterly GDP series filtered using a band pass filter. The GDP series are mostly drawn from the OECD's Quarterly National Accounts publication, supplemented by national sources. The band pass filter used is described in Baxter and King (1999) and discussed in further detail in Chapter 3.

[6] See Chapter 2 for more details on defining recessions.

nearly any point in time, output in some countries is above trend, while in others it is below trend. In other words, a very heterogeneous set of countries has adopted a common currency in 1999. In the short run, this may not be a problem for monetary policy decisions since the ECB only needs to worry about economic developments in the euro area as a whole. In the long run though, it will be difficult for a country to be part of a monetary union if its business cycle is not (broadly) in line with that of other member countries.

A problem that does surface in the short run is that GDP estimates are made quarterly and released with substantial delays whereas the ECB has to set its benchmark interest rates each month. It is therefore useful to have more frequent and timely estimates of the state of the economy by way of business cycle indexes. These indexes are meant to reflect the current state of the economy and its likely development in the near future by using data that are more frequently available and timelier than GDP data. One can choose from a wealth of series that are generally available at a monthly frequency: industrial production, sales, consumer and business confidence, etc. For policy makers, it is relevant how these data can best be combined into an informative index of the state of the economy. This question is even more pressing for the euro area since less is known about the structure of this economic area as a whole. Particularly given the less than perfect correspondence between country cycles, it is important to know how much information is lost when focusing on a dataset of limited size for the largest euro area countries.

Chapter 2 examines how many different series are needed to get a good description of the euro area business cycle. The main finding in this chapter is that an index based on a relatively limited amount of economic series (less than forty) for France, Germany and Spain is able to capture the main cyclical facts for the euro area. However, another finding is that comparable variables in different countries have different effects. For example, German industrial production is much more important in explaining movements in euro area GDP than comparable series for France and Spain. This again brings the heterogeneity from Figure 1.1 to mind.

Although this heterogeneity is not crucial for short run policy making, in the long run, the monetary union is at risk if the common monetary policy is not suitable for most countries, most of the time. Of course it is not always the same country that has either the maximum or minimum output gap in Figure 1.1, so it is useful to look at the correlation of (detrended) output of each country with euro area output.[7] As Table 1.1 shows, the correlation with the euro area aggregate is on average higher for euro area countries than for the other countries in the table. However, this still leaves some countries with either an unrelated business cycle (Greece) or relatively low correlations (Finland, Portugal, Spain). On the other hand, although countries like Switzerland or Norway are not part of the European Union, they both had a business cycle that closely resembled the euro area cycle.

Table 1.1 Output correlation of European and non-European countries with the euro area, 1999-2003

Euro area countries (average: 0.65)			
Austria	0.78*	Ireland	0.81*
Belgium	0.83*	Italy	0.95*
Finland	0.47*	Netherlands	0.71*
France	0.98*	Portugal	0.47*
Germany	0.97*	Spain	0.47*
Greece	-0.26		
Other countries (average: 0.38)			
Australia	-0.57*	Norway	0.63*
Canada	0.44	Sweden	0.57*
Denmark	0.64*	Switzerland	0.91*
Japan	0.63*	UK	0.65*
New Zealand	-0.25	US	0.17

Source: OECD Quarterly National Accounts, supplemented with Eurostat data for Denmark, Italy, Norway, Sweden and Switzerland, for Japan with data from the Cabinet Office (SNA68 series), for Spain from INE (SNA68 series) and for Canada with data from Statistics Canada.

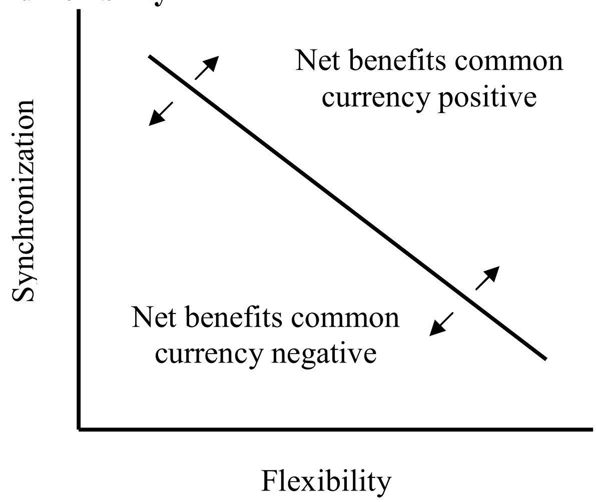
Notes: Correlations between band pass filtered quarterly GDP for each country and the euro area aggregate. The euro area aggregate excludes the country in question for euro area correlations. * denotes a correlation significantly different from zero at the 5% level.

While Table 1.1 shows that the business cycles of euro area countries are not perfectly correlated with the euro area aggregate, this may not be a big problem if the

[7] Comparing (detrended) output of individual countries to the euro area aggregate would bias the correlations, since the country is part of the euro area aggregate. Therefore, each country is compared to an aggregate of all euro area countries, excluding the country under analysis.

economies in each country are flexible enough to adjust through a high mobility of capital but especially of labour. To see why this is the case, imagine that one of the euro area countries is hit by an adverse demand shock to its main export products. As a result, workers in the export industry will become unemployed and the country as a whole may enter a recession. However, if unemployed workers can easily find employment in a euro area country with excess demand for its products, the adverse effects will be much smaller for the first country. This underpins the idea that the costs of a common currency will be low when business cycles are very similar or when the economies are flexible enough to adjust to asymmetric shocks. In a recent paper, de Grauwe and Mongelli (2005) show this relationship in the following way.

Figure 1.2 The costs of a common currency for different levels of synchronization and flexibility



Source: De Grauwe and Mongelli (2005)

The net benefits of adopting a common currency depend to a large extent on these two dimensions discussed above.[8] De Grauwe and Mongelli (2005) argue that the euro area has the right combination of synchronization and flexibility, while the European Union as a whole falls short. While the exact net benefits are hard to establish, Chapter 3 examines whether euro area countries will become more synchronized as economic and monetary integration increases. If synchronization is likely to rise under monetary union,

[8] De Grauwe and Mongelli (2005) also look at the degree of economic integration, a topic which is discussed in more detail later.

the pressure for greater flexibility might decrease – at least from the perspective of the cost of the euro.

The effect of monetary integration on synchronization may be evaluated directly by examining whether more stable exchange rate regimes in Europe over the past decades have led to more synchronized cycles. After the demise of the Bretton-Woods golden-dollar standard in the early 1970s, exchange rates were allowed to be determined by market forces. However, within Europe, arrangements like the Exchange Rate Mechanism (ERM) were set up to stabilize exchange rates from the late 1970s onwards, culminating in the launch of the euro in 1999. A test of the impact of monetary integration is to see whether business cycles have become more similar as exchange rates have become more stable over time. A second approach to this problem is to look at the long run experience of business cycles within an existing monetary union. Since the U.S. is similar in size to the euro area, the history of business cycle synchronization between its states provides useful information. Finally, to draw policy-relevant conclusions, it is necessary to know the determinants of synchronization. Of specific interest is the importance of coordinated monetary and fiscal policy relative to trade links and other structural economic characteristics such as specialization in explaining synchronization. These factors are important because in addition to common monetary policy between EMU countries, differences in fiscal policy are also (to some extent) kept in bound through the Stability and Growth Pact. In addition, one might expect trade links to become stronger due to fixed exchange rates and specialization. Chapter 3 aims to disentangle how each of these consequences of economic integration affects business cycle synchronization.

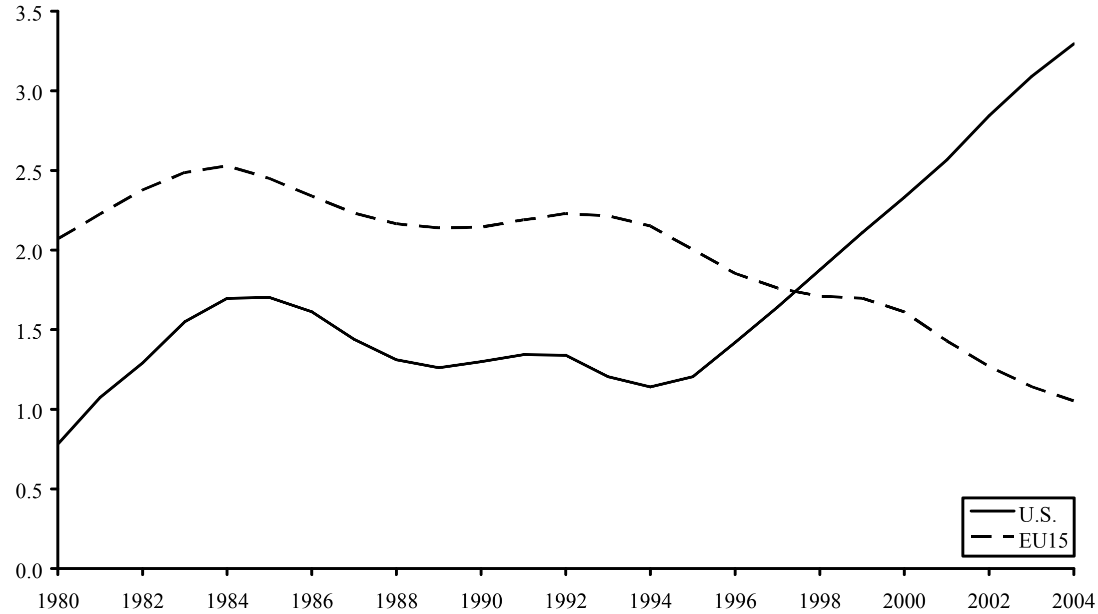
The analyses in Chapter 3 show that there is no strong trend towards ever greater synchronization, neither in Europe nor in the United States. However, as Table 1.1 showed, the degree of synchronization within the euro area has been higher than between OECD countries in general, and this has been the case since the mid 1980s. More coordinated monetary policy and more stable exchange rates have contributed to this development, as have more similar trade flows, fiscal policy and a greater degree of financial integration. As the monetary union becomes more established, synchronization is likely to increase even further, to levels similar to those between U.S. states. These results suggest that the costs of the euro are likely to be sufficiently low to sustain political support for the euro. There are important uncertainties though, mainly about whether fiscal policy will remain relatively similar and to what extent specialization will increase or decrease. These uncertainties argue for greater flexibility of European economies, as well as the fact that a greater degree of flexibility will increase the net benefits of monetary union (Figure 1.2). In addition, research for the U.S. by Kim (1995) has shown that specialization tends to decrease as production factors more mobile. Furthermore, measures to stimulate (cross-border) labour mobility will also improve European competitiveness by making it easier to exploit new technologies.

1.3 Competitiveness in Europe

In the long run, the only way to increase income per head of population is to increase productivity. In general, per capita income can increase because a) a greater share of the population is employed, b) employed persons work more hours or c) output per hour worked increases. While there are natural limits to the employment rate and average hours worked, productivity growth is in principle unbounded. This makes it particularly worrisome that over the past decade, labour productivity growth in Europe has slowed down, while U.S. growth accelerated.[9]

[9] A low employment rate is also among the challenges facing Europe, but this is not dealt with in detail in this thesis. See e.g. Garibaldi and Mauro (2002) and McGuckin and van Ark (2005).

Figure 1.3 Trend growth in GDP per hour worked in the EU-15 and U.S., 1979-2004



Source: GGDC (2005a) Note: trend is estimated using Hodrick-Prescott (1997) filter on productivity growth

Figure 1.3 plots trend labour productivity growth for Europe and the U.S. for the period 1979-2004.[10] The figure shows that European growth outstripped U.S. growth for most of this period, but the roles have reversed since the mid-1990s. From 1995 onwards, there is a clear rise in U.S. trend growth, while the European trend has been decreasing. Table 1.2 shows that despite much faster GDP growth, U.S. productivity growth outpaced European growth by a small margin during the 'boom'-period between 1995 and 2000 because of the strong growth in U.S. hours. After 2000, GDP growth decreased in both Europe and the U.S., but the productivity growth gap widened substantially. The upside of this development is that European employment growth has been higher than in the U.S. since 2000. This could mean that Europe has 'traded off' productivity growth for employment growth. But one might as well turn this conclusion around and ask why GDP growth has not increased in line with higher employment growth.[11]

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[10] The underlying data are from the GGDC (2005a) Total Economy Database. The trend is estimated using a Hodrick-Prescott (1997) filter. Note that as with any filter, the estimates for the beginning and end of the sample are less reliable than the other years. This mostly affects the first and last two years. When one is only interested in long-run trends, the Hodrick-Prescott filter is somewhat more convenient than the band pass filter used for Figure 1.1. As Chapter 3 describes in detail, the differences are generally not large.
[11] For more on the relationship between productivity and employment growth, see McGuckin and Van Ark (2005).

Table 1.2 Growth of output, employment and productivity in Europe and the U.S., 1987-2004

	EU-15			U.S.		
	1987-1995	1995-2000	2000-2004	1987-1995	1995-2000	2000-2004
GDP growth	2.2	2.7	1.4	2.7	4.0	2.5
Growth in total hours worked	0.0	0.9	0.4	1.6	1.9	-0.4
Growth in GDP per hour worked	2.2	1.8	1.0	1.1	2.1	2.9

Source: GGDC (2005a)

By now, most researchers agree that ICT has played a key role in the post-1995 productivity acceleration in the U.S., partly through strong productivity growth in the ICT production sector and partly through an ICT investment boom across the economy. Chapter 4 quantifies and analyzes these effects for both the American and European economies and asks why European growth has not taken off in tandem with the U.S. In an accounting sense, U.S. productivity growth has outstripped European growth because ICT production is a larger sector in the U.S. and because ICT investment has been higher than in Europe. However, a considerable fraction of the growth gap cannot be traced to a rise in capital or labour input and is labelled as total factor productivity (TFP) growth. TFP growth has been especially important in raising the contribution of market services to aggregate labour productivity growth.

To shed light on the role of TFP growth in understanding the productivity gap between the U.S. and Europe, one of the assumptions underlying the neoclassical growth accounting framework is relaxed. Instead of assuming that the marginal productivity of ICT capital is equal to its marginal cost, econometric techniques are used to estimate the marginal product. It turns out that the marginal product of ICT has followed a U-shaped pattern over time. Up to the early 1980s, ICT capital returned its marginal cost, but since then it turned negative. It was not until the start of the 1990s that the productivity and costs of ICT capital came back into balance again. Furthermore, these developments occurred a few years earlier in the UK and U.S. than in France, Germany and the Netherlands.

One explanation for this pattern is that the relatively straightforward savings from ICT were realized early on in the diffusion process. However, additional productivity gains first required complementary innovations in organizational change and (unmeasured) investment in intangible capital. This appears of particular importance in services industries. An example can be found in retail trade. While it has been relatively straightforward to adopt barcode scanning in supermarkets to speed up check-out, it has been much harder and time-consuming to reorganize the supply chain and take advantage of the increased information on customer purchases. As a result, after the initial cost savings, it took a long time before a noticeable impact on productivity could again be found. It can be argued that restrictive product and labour market regulation are important reasons for lagging ICT diffusion in Europe. Such regulations may have hampered complementary innovations, making ICT investment less profitable.[12]

While Chapter 4 focuses on structural explanations for differences in productivity growth, cyclical factors cannot be discounted out of hand. Figure 1.3 showed productivity growth trend estimates because year-to-year changes in productivity tend to fluctuate, obscuring longer run patterns.[13] These fluctuations are not just random noise. Productivity growth tends to be procyclical, i.e. it is generally higher during economic expansions than during recessions. As a result, some have argued that business cycles are caused by technology shocks, the so-called Real Business Cycle theory. Another explanation for procyclicality is that firms may decide not to immediately fire workers during downturns in demand, but instead 'hoard' those workers until economic conditions improve. Chapter 5 examines a number of explanations for cyclical productivity for three European countries and the United States.

The analysis in Chapter 5 relaxes two key assumptions commonly used in the empirical productivity literature, namely constant returns to scale (if all inputs increase by one percent, output is assumed to increase by that same one percent) and exact measurement of labour and capital input. Instead, the analysis allows for variable returns to scale and unmeasured variation in capital utilization and labour effort. The results provide only limited statistical evidence against constant returns to scale and well-measured inputs. Furthermore, even when taking the limited evidence at face value, productivity appears still procyclical in many industries. Most relevant for this study, the stylized facts about productivity growth do not change when allowing for variable returns

[12] See McGuckin, Spiegelman and van Ark (2005) for more on productivity growth in retail trade.
[13] See also Inklaar and McGuckin (2003) on this topic.

to scale or unmeasured input utilization, confirming the importance of supply-side factors.

1.4 An agenda for reform

Although there are still important gaps in our understanding, the research presented in this study points at a number of directions in which European economic performance can be improved. Foremost among these are reforms to foster flexibility of product and labour markets. European firms are exploiting new technologies at a much slower rate than their American counterparts and as a result, Europe is missing out on potential productivity growth. Removing barriers to entry and growth of new firms can help spur ICT investment and foster the necessary complementary innovations. It should also become easier for existing firms to, for example, open up new branches or try out new business concepts without wading through endless reams of red tape. Further efforts at freeing up trade in services will also make it easier for successful firms to achieve sufficient scale. In a similar fashion, a more flexible workforce makes it less costly when experiments do not work out in practice. All these measures feature in the Lisbon reform agenda, and although implementation is still patchy, the research in this book shows that based on the experience of the U.S., the potential gains are large.

As discussed earlier, flexibility also improves the cost-benefit analysis for using a common currency. So in addition to stimulating competitiveness, reforms aimed at more flexible product and labour markets also reduce the costs of a common currency. It seems likely that synchronization of business cycles will be high enough for the costs of the EMU to remain containable, but this is contingent on a stable or decreasing degree of specialization and coordinated fiscal policy. Strict deficit rules are not all that important in this respect, but the more qualitative rule to keep cyclically-adjusted deficits at or above zero should contribute positively to synchronization. Reforms that enhance the flexibility of European labour markets will increase the freedom of movement for government policy.

Chapter 2 The euro area business cycle[14]

2.1 *Introduction*

The European Central Bank (ECB) is charged with maintaining price stability in the euro area and to set monetary policy, it needs information about the state of the euro area economy. A business cycle index (BCI) can provide this information at a glance. However, BCIs have mainly been developed for the U.S., with much less research focusing on the euro area. In case of the euro area as a whole, an added complexity is that it only recently became an economic entity in its own right due to the ECB's common monetary policy. The scarcity of research does not leave the ECB or other policy makers without tools to analyze the euro-economy: there is an area-wide structural model (see Fagan, Henry and Mestre, 2005) as well as more recent work on Bayesian dynamic general equilibrium models (Smets and Wouters, 2004). However, BCIs are a useful complement as they do not rely on a detailed description of the economic structure and do not make assumptions regarding the behaviour of consumers or firms. Rather, BCIs are constructed based on statistical analysis of the economy in question.

This chapter compares different methods of constructing BCIs. The main question it addresses is how the selection of a set of variables affects the performance of different BCIs. In a recent paper Boivin and Ng (2003) also address this issue and, using simulation techniques, they come to the conclusion that indexes, which are based on a limited number of variables, perform at least as well or even better than those based on the full dataset they consider.[15] The analysis here is largely complementary: the setting is applied and uses economic logic rather than statistical algorithms to reduce the data set.

The comparison of BCI construction methods focuses on ability of BCIs to capture relevant historical cyclical facts, not on their performance in real-time forecasting.

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[14] This chapter is largely based on Inklaar, Jacobs and Romp (2003). See acknowledgements for further details.

[15] Bai and Ng (2002) also find that the number of series need not be very large to get precise estimates for factor models, one of the methods used in constructing BCIs.

Furthermore, the turning points of the index are considered to be the most relevant cyclical fact, although others would focus on, for example, the business cycle as a periodic cycle or a serially correlated phenomenon.[16] To evaluate forecasting performance, an analysis would be needed along the lines of e.g. Diebold and Rudebusch (1991) or McGuckin, Ozyildirim and Zarnowitz (2003) and more attention would need to be paid to end-of-sample problems as in Forni, Hallin, Lippi and Reichlin (2003).

The methodology for constructing BCIs was originally developed at the National Bureau of Economic Research (NBER) in the U.S. in the 1930s and described in the seminal book of Burns and Mitchell (1946). It has since then been widely used (see e.g. Zarnowitz, 1992). In recent years these "NBER method" indexes are maintained and regularly published by The Conference Board (TCB), which has also developed similar indexes for other countries. A more recent development in the construction of BCIs is the use of dynamic factor models. Early applications of dynamic factor models are described in Sargent and Sims (1977) and Geweke (1977). Recent examples are Stock and Watson (1989, 2002), Camba-Mendez, Kapetanios, Smith and Weale (2001), and the Generalized Dynamic Factor Model of Forni, Hallin, Lippi and Reichlin (2000) and Forni and Lippi (2001).

After a general introduction to business cycle measurement, Section 2.2 describes the two different methods used for constructing BCIs, namely the generalized dynamic factor model of Forni *et al.* (2000) and the NBER method. Section 2.3 presents three BCIs for the euro area. The first uses a relatively small dataset and is constructed using the NBER method (EuroTCB). The second is estimated using a dynamic factor model and a very large dataset (EuroCOIN from Altissimo *et al.*, 2001). The final index is based on a small dataset and constructed using a dynamic factor model (EuroIJR). This final index can be used to gauge the relative importance of data selection to arrive at a small dataset on the one hand and the method of index construction on the other hand. Section 2.4 compares the three business cycle indexes in terms of how they are correlated and track the euro area cycle. In Section 2.5 the EuroIJR index is used to shed some light on cyclical dynamics in the euro area.

[16] See Harding and Pagan (2005) for an overview of these approaches.

The main finding is that the business cycle indexes analyzed here are very similar in terms of correlations. The dates of peaks and troughs are also similar. The leads and lags around the turning points of euro area GDP are generally modest and none of the three indexes is consistently more accurate in pinpointing peaks and troughs than the other two. This suggests that a useful BCI can be constructed using only a limited number of variables. Furthermore, it is not necessary to include data from each euro area country to adequately capture the euro area cycle. As Chapter 1 already showed, cycles of European countries tend to move together and the analysis in this chapter confirms that for some purposes, the differences across euro area countries are not crucial and the area can be treated like a single economic entity.

However, the analysis of cyclical dynamics brings some of the heterogeneity of the different countries to the fore. So, for example, German industrial production is one of the most important variables in the EuroIJR index, whereas French and Spanish industrial production make only modest contributions to the index. This means that a shock to German industrial production tends to have a different effect on the euro area cycle than similar shocks in France and Spain. So even for short-run policy making, the euro area cannot be treated as fully homogeneous.

2.2 Methodology

Business cycles are more or less regular patterns in fluctuations in economic activity. In the well-known definition of Burns and Mitchell (1946, p. 3):

> A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own.

In other words, expansions and contractions in economic activity are observed in time series of many variables across different sectors of most (market) economies at roughly the same time. This suggests that an index capturing these movements would be very useful. This idea lies at the core of the NBER approach as originally proposed by

Burns and Mitchell (1946). An alternative method to measure business cycles is to formulate a formal statistical model which identifies underlying “shocks” that drive the business cycle.[17] Dynamic factor models are part of this latter group and provide a more formal way to select and weight relevant cyclical variables. This chapter will compare business cycle indexes constructed according to both approaches.

Burns and Mitchell (1946) define the business cycle in terms of fluctuations in economic activity. However, the choice of a measure of "economic activity" is not straightforward. The usual choice is GDP, but since GDP is only available on a quarterly frequency, additional variables are needed to establish a monthly chronology. Furthermore, the usual publication lag of GDP makes it unsuitable for gaining a timely insight into the state of the economy. Therefore, the NBER Business Cycle Dating Committee has adopted a broader approach in the U.S. by also looking at other (monthly) economic variables such as industrial production or retail sales.

Contractions of economic activity are an essential ingredient of the classical definition of a business cycle. However, some economic theories predict movements around a permanent component or “trend”. This has given rise to the analysis of fluctuations around a trend, a category of cycles usually referred to as deviation cycles or growth cycles. While policy makers are primarily interested in classical cycles, academics tend to focus on deviation cycles (Harding and Pagan, 2000). A third type of cycles looks at turning points in the growth rate of economic activity. These growth rate cycles are related to deviation cycles, since growth rates can be interpreted as a trend filter (cf. Harding and Pagan, 2005).

Given a reference series of economic activity, turning points of business cycles can be determined in levels, deviations from trend, or growth rates. This chapter focuses on the classical cycle and the growth rate cycle concepts, as discussed further below. The deviation cycle is central to the next chapter and the main methods are described there. The standard method to determine turning is to use the algorithm of Bry and Boschan (1971). This algorithm calculates moving averages of different lengths to narrow down

[17] The term "shock" should not be taken to mean that business cycles are set in motion through economic events such as, for example, stock market crashes or technology shocks. In a purely statistical sense, a shock is a phenomenon that causes a variable to diverge from its long-run average.

the region where the turning points are likely to be located and then pinpoints the exact month where the peak or trough occurred using the original series. The only restrictions are that a full business cycle (peak to peak or trough to trough) should last at least fifteen months, each business cycle phase (peak to trough, trough to peak) should last at least five months and peaks and troughs should alternate. These criteria have been developed to pinpoint turning points in the classical business cycle using monthly data. A generalization to quarterly or even annual data is relatively straightforward, as discussed in Harding and Pagan (2001). Application of the Bry-Boschan algorithm to the dating of growth rate cycles is less well established, mostly because no independent reference chronology exists for a growth rate cycle, as is the case for the classical cycle in the United States. However, Zarnowitz and Ozyildirim (2001) have recently used the Bry-Boschan algorithm to compare various filtering methods and the algorithm is also applied to the dating of EuroCOIN turning points (see Altissimo *et al.*, 2001).[18] In this chapter, the same rules are used for dating growth rate cycles as for dating classical cycles, but further research on the appropriateness of this choice is called for.

The NBER method

In establishing a monthly business cycle chronology, the NBER relies on four monthly variables: employment, personal income, industrial production and manufacturing and trade sales. Together these make up the composite coincident index for the United States. The choice of these variables (in some form) can be traced back to the work of Burns and Mitchell (1946). Since then, the four components of the coincident index have stood up as a good representation of the reference business cycle.

Potentially relevant economic variables are evaluated based on how closely they track the classical cycle of the reference series. This can be done by looking at the correlations with the reference series at various leads and lags and whether variables exhibit peaks and troughs around the same time as the reference series. Consistently leading and lagging variables are then combined into leading and lagging composite indexes. The change in a composite index is calculated as the unweighted average of

[18] In contrast, Artis, Marcellino and Proietti (2002) identify periods with negative growth rates for a certain number of months as a recession.

changes in the components, after normalisation; the level of the index is computed by cumulating the changes from a specified base year.[19]

The choice of variables depends for a large part on the judgment of the researcher. One has to construct a "good" reference series based on a measure of "economic activity", find a way to determine its peaks and troughs and then evaluate whether other variables have a "close" relationship to the reference series. The degree of subjectivity of the NBER method has been a motivation to develop more statistically oriented methods.

The Generalized Dynamic Factor Model

Although statistical methods also involve a number of (subjective) choices, generally speaking they do impose more (theoretical) structure on the problem of measuring business cycles. The basic idea of factor models is that a dataset consisting of a number of time series can be decomposed into a common component and an idiosyncratic component, where the common component is driven by only a few common shocks. Although many factor models fit this general description, the remainder of the analysis uses the Generalized Dynamic Factor Model (GDFM) of Forni *et al.* (2000). The model is "generalized" in the sense that, contrary to the earlier dynamic factor models such as those of Sargent and Sims (1977) or Geweke (1977), the idiosyncratic components can be correlated.[20] The factor model is basically a method of rank-reduction, where the information in the large matrix of observations is summarized in the matrix of common components of smaller rank.[21] The GDFM can be written as follows.

(2.1) $$x_{it} = \chi_{it} + \xi_{it} \equiv b_{i1}(L)u_{1t} + b_{i2}(L)u_{2t} + \ldots + b_{iQ}(L)u_{Qt} + \xi_{it},$$

where x_{it} is the t-th observation on the i-th time series and L is the lag operator. The dynamic factor loading $b_{ij}(L)$ describes the dynamic impact of the j-th common shock u_j on the i-th series. The common shocks and the factor loadings together make up the *common components* $\chi_{i,t}$. After the influence of common shocks has been removed, only

[19] See The Conference Board (2001) for more details

[20] The theoretical criterion is that idiosyncratic shocks can be correlated as long as this correlation can still be distinguished from the common shocks. In practice, it is harder to draw a strict line. See the appendix to this chapter for more details.

[21] A more extensive discussion can be found in Appendix 2.A.

the idiosyncratic components ξ_i remain. Equation (2.1) shows that the model is explicitly dynamic since a common shock can affect a variable with leads or lags.

As Forni *et al.* (2000) show, the common component in this model is only uniquely identified in a dataset with an infinite number of observations and time series, but they present an estimator that is reasonably precise for datasets of more modest dimensions. The main identifying assumption is that there are only a limited number of common shocks that explain an increasing percentage of the variance of the dataset as the number of time series in the dataset grows, while the importance of the idiosyncratic shocks remains bounded. The common components of Equation (2.1) can then be estimated by employing principal component analysis in the frequency domain.

The common component of a series is the part that is driven by shocks that are common to all series, while the remainder is idiosyncratic noise. The common component of GDP is the logical candidate for a business cycle index. Abstracting from mathematical complexities, the common component of a series is a linear combination of all the variables, where the weights on each of the variables are chosen to maximize the variance explained by the common component. Since the main interest is in cyclical fluctuations we also want to filter out the high-frequency noise of GDP's common component:

$$(2.2) \qquad x_{it} = \chi_{it}^{C} + \chi_{it}^{NC} + \xi_{it} = \sum_{n=1}^{N} \sum_{m=-M}^{M} K_{i,n,m}^{C} x_{n,t+m} + \chi_{it}^{NC} + \xi_{it} \, ,$$

where K_i^C is the matrix of weights used in calculating the cyclical common component χ_{it}^C. Weights are available for each variable *i* and each lead and lag, denoted by *m*. A similar decomposition can also be made for the irregular, high-frequency noise in χ_{it}^{NC}.

Instead of the GDFM, other factor models could have been used as well, but there are a number of reasons for using the GDFM. First, an important characteristic of business cycles is that not all variables move exactly in phase: leads and lags are quite common. This makes it essential to use a dynamic factor model, to take these leading and lagging relationships into account. Second, in the model of Forni *et al.* (2000) it is very straightforward to remove high-frequency noise and only focus on longer run fluctuations. Finally, the GDFM allows for a certain amount of correlation between idiosyncratic components. This can be very important for cyclical indicators. For example, if two industrial production series are included in the index, it is quite possible that measurement errors in the two series are partly correlated, although both of these measurement errors are unrelated to cyclical fluctuations. If idiosyncratic components were required to be strictly uncorrelated, part of this measurement error would show up in the common component. To avoid this, it is desirable to allow for some amount of correlation between idiosyncratic components. A more pragmatic reason for choosing the GDFM is that this way, a more parsimonious specification of the EuroCOIN index can be compared to EuroCOIN.

The GDFM is basically a multivariate filter for euro area GDP. The information from other series allows the model to a) eliminate idiosyncratic measurement errors, b) filter out high-frequency noise, c) estimate economic activity within a quarter and d) use information from leading variables and their relation to GDP to forecast economic activity for recent periods. Although the final point is quite important for the usefulness of a BCI, the model applied here is only equipped to take the first three points into account.[22]

One problem in applying this method is that the selection of the number of common shocks is not straightforward; see also Bai and Ng (2002). Here, one of the criteria suggested by Forni *et al.* (2000) is used, namely that each common shock should explain at least a pre-specified percentage of total variance.[23]

2.3 Euro Area Business Cycle Indexes

This section describes three business cycle indexes for the euro area: EuroTCB, a coincident index constructed along the lines of the NBER methodology, EuroCOIN, in which the Generalized Dynamic Factor Model is applied to a large set of data, and the hybrid EuroIJR, in which the GDFM is used on the limited set of variables used in the construction of coincident and leading indexes for European countries by TCB. EuroCOIN is constructed by others and published online monthly, but EuroTCB and

[22] See Forni *et al.* (2003) for details on end-of-sample estimation.
[23] See Appendix 2.A for further discussion.

EuroIJR were specifically constructed for the analysis here. In all cases, quarterly GDP for the euro area is included in the construction of the index. The information from the other series is used to get the information that is necessary for a monthly business cycle chronology.

EuroTCB

The Conference Board (TCB) publishes business cycle indexes for a number of euro area countries on a monthly basis. At present, coincident and leading indexes are constructed for France, Germany and Spain. The components of the coincident indexes have been selected based on the components of the U.S. coincident index as well as their ability to match the business cycle turning points of GDP in the individual countries. The leading indexes have been constructed so that they generally lead the coincident index at business cycle turning points.

The components of the leading and coincident indexes differ across countries, but they generally contain the same type of time series. The coincident indexes include measures of sales, income, production and employment. The leading indexes usually contain financial variables such as bond yields and share prices, natural leading series like orders for new goods and building permits, and finally surveys of consumer or business confidence.[24] All series have been selected to match classical cycle turning points in each of the individual countries. It is therefore not clear whether they will provide a good representation of the euro area growth rate cycle, but given that these three countries account for about 60 percent of euro area GDP, the representation is assumed to be reasonably good.

In constructing the EuroTCB index the NBER and TCB procedures are followed as well as possible.[25] The procedure starts off with 12 coincident variables, four from each country, and euro area GDP from the OECD Quarterly National Accounts. In the construction of a monthly index, the quarter-on-quarter growth rate of GDP is applied to each month in the quarter. This procedure corresponds to linearly interpolating the level

[24] Table 2.4 below provides a list of the components of the leading and the coincident indexes for the three countries

[25] For a more extensive discussion of the methods, see The Conference Board (2001).

of GDP for each month.[26] To construct a BCI for a country, The Conference Board weights each series by a standardization factor. This standardization factor is calculated from the inverse standard deviations of each of the series, normalized to sum to one. An analogous procedure is followed here for the 12 variables plus euro area GDP.[27] It would be possible to weight by the relative size of the economies in addition to the relative volatility of each series. However, only using the relative volatility is more in line with the NBER tradition and it is also more in line with the procedures used in calculating the other two BCIs. According to Altissimo *et al.* (2001), EuroCOIN is calculated from a set of series after normalizing and in calculating the EuroIJR index we also do not perform further weighting. Euro area GDP in the index is included mostly to make the index more comparable to the other two. However, the index including and excluding euro area GDP are very similar (correlation of 0.99) and the turning points are never more than a few months apart.

EuroCOIN

The EuroCOIN index is published monthly by the Centre for Economic Policy Research (CEPR) (www.cepr.org). Altissimo *et al.* (2001) describe the index in detail, so only the highlights are covered here. The authors construct their index from a database with monthly observations for 951 series for France, Germany, Spain, and Italy, the Netherlands, Belgium and a number of euro area wide variables. Using a number of criteria, such as timeliness in publication and concordance to the common shocks, they reduce their dataset to 246 series. The series cover a wide range of variables such as industrial production, prices, interest spreads and surveys of business and consumer confidence. The generalized dynamic factor model is applied to this database, after first differencing to render the series stationary. The authors include all common shocks that capture 10 percent or more of total variance, which leads to the choice of four factors. The first four dynamic principal components together explain 55 percent of all variance

[26] An alternative would be to interpolate the growth rates instead of the level. There is no strong case for either of these options, but at least for the chosen procedure, it is immediately clear that the month-to-month developments in GDP are not known, since the same growth rate for each month is used.
[27] To be precise, the month-on-month changes in each of the variables are multiplied by the standardization factor and summed across variables. For comparability to the other two BCIs, the 3-month average of this summation is used as the index.

in the data. Altissimo *et al.* (2001) then use the cyclical part of the common component of euro area GDP as their business cycle index, i.e. all fluctuations with a periodicity higher than 14 months. Due to the stationarity requirement of the GDFM, GDP is included in growth rates, so their BCI models the growth rate cycle of the euro area.

EuroIJR

For the third euro area business cycle index, the generalized dynamic factor model is applied to the components of the coincident and leading indexes for France, Germany and Spain of TCB. In the construction of this index, which is referred to as EuroIJR, features from both approaches are combined.[28] On the one hand, data is used that analysts consider as informative for the cyclical development in euro area countries. The turning points of these series generally lead or coincide with GDP of the country in question. The fact that only a limited number of series enters into the index makes it easier to relate changes in the index to changes in the components and therefore to interpret these changes. On the other hand, the GDFM is used to weight the series. This way, we can examine whether selecting only a limited number of variables for the index leads to a serious loss of information. Note that TCB has selected the coincident and leading variables to match classical turning points in economic activity, without reference to turning points in the growth rate cycle. It is therefore possible that some other variables would be selected if this latter cycle concept were used. This possibility is not investigated further, but left for further research. It should be noted though, that a selection based on the correspondence to the growth rate cycle may even improve the performance of the index.

In total, 37 indicators enter into the coincident and leading indexes of France, Germany and Spain (see the overview in Table 2.4). For each country, there are four coincident series. For France, the leading index contains ten indicators, while the corresponding indexes for Germany and Spain contain eight and seven series respectively. In addition to these variables, we include quarterly GDP growth for the euro

[28] The IJR in EuroIJR refers to the initials of the authors of the original paper on which this chapter is based, Inklaar, Jacobs and Romp (2004).

area. All series are analyzed as normalized exponential growth rates (first differences in logs), since stationarity is a prerequisite to the GDFM.

As mentioned above, the criterion of Forni *et al.* (2000) is used with common shocks included as long as they explain at least five percent of total variance. This leads to the selection of six common factors that together capture fifty percent of total variance and sixty percent of cyclical variance in the data. Just as in Altissimo *et al.* (2001), all fluctuations with a frequency lower than 14 months are defined as cyclical.

2.4 Comparison

This section compares the three BCIs for the euro area, looking at the period from January 1988 to September 2002. The data from The Conference Board are available for a longer period of time but EuroCOIN only starts in 1988, which limits the time span for comparison. Some other differences between the indexes are also of interest. EuroCOIN covers the widest range of countries, namely Belgium, France, Germany, Italy, Netherlands and Spain; the other two indexes only include data from France, Germany and Spain. As a result, EuroIJR and EuroTCB are based on data from countries representing 60 percent of euro area GDP, while EuroCOIN's countries cover nearly 90 percent. Although all three BCIs include euro area GDP as one of the components, the GDP series used to construct EuroCOIN seems slightly different from the series used for the other two indexes (compare Figure 2.1 and Figure 6 from Altissimo *et al.*, 2001).[29] Finally, the EuroIJR index is based on the first six common factors, while EuroCOIN is based on four factors. Given the differences in the two datasets, these factors are not comparable. However, the resulting index is qualitatively similar whether four or six common factors are selected.

In the remainder of this section the three BCIs are compared in terms of their correlation with GDP growth and in terms of cyclical peaks and troughs, both in the classical cycle and the growth rate cycle. The euro area classical cycle is defined by the peaks and troughs of euro area GDP. Figures 2.1 and 2.2 show monthly series of euro

[29] The GDP series used by Altissimo *et al.* (2001) could not be acquired, but visual inspection of the two GDP series does not reveal any major discrepancies.

area GDP and the BCIs.[30] Figure 2.1 shows euro area GDP and the three BCIs as indexes with January 1988=100. The euro area growth rate cycle is defined by the growth rate of euro area GDP and consequently all three BCIs are taken as growth rates, (Figure 2.2). In both sets of figures the area between cyclical peaks and troughs is shaded. In Figure 2.1, these correspond to classical business cycle recessions, in Figure 2.2 these correspond to periods of declining growth rates. To determine the turning points the algorithm of Bry and Boschan (1971) is used.[31] Although the figures show differences in short-term fluctuations, overall the similarities between the indexes are striking. Especially the recession of 1993 clearly stands out in all three indexes.

Table 2.1 shows the correlations between the three indexes (in growth rates) as well as the change in euro area GDP. Correlations are based on the monthly series and the quarterly aggregates. The quarterly results are included because for GDP only quarterly data is available, whereas monthly GDP is interpolated. For the correlation coefficients this interpolation has little or no effect. The correlations confirm the conclusions from visual inspection by showing large and positive coefficients (all significant at the 1 percent level). In other words, the three indexes all capture a large amount of the variation in euro area GDP since 1987.

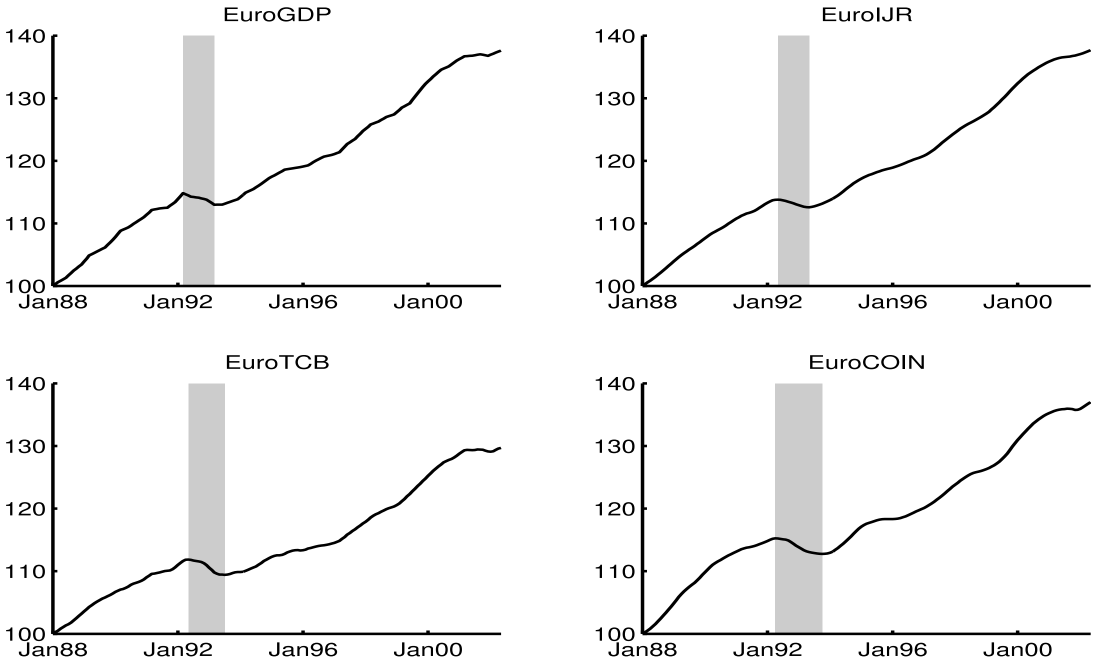
[30] Appendix 2.B shows the same type of figures for quarterly aggregates of the indexes. The quarterly series are calculated as the average of each of the indexes within the quarter. For EuroTCB and EuroIJR the basic data could also be aggregated to a quarterly frequency and the indexes calculated from these new series, but this changes littles.
[31] The program implementing the Bry-Boschan algorithm is taken from Mark Watson, converted from Gauss to Matlab and adapted along the lines of Harding and Pagan (2001) to also determine turning points in quarterly series.

Table 2.1 Correlation between euro area GDP and business cycle indexes

	EuroGDP	EuroIJR	EuroTCB
Monthly index			
EuroIJR	0.84		
EuroTCB	0.80	0.88	
EuroCOIN	0.80	0.92	0.84
Quarterly index			
EuroIJR	0.84		
EuroTCB	0.83	0.91	
EuroCOIN	0.80	0.93	0.86

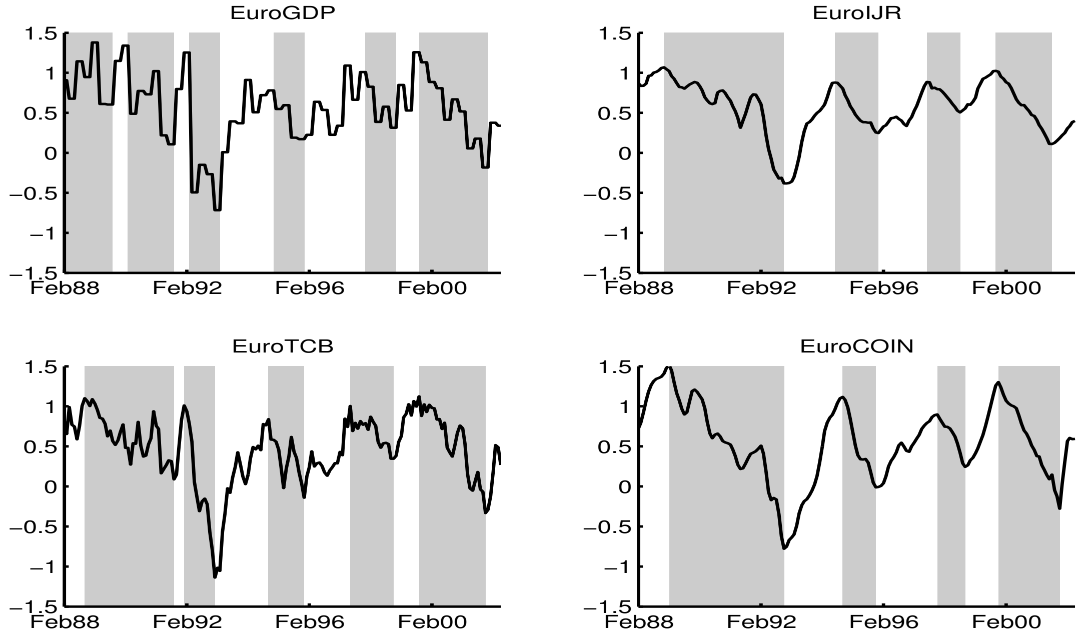
Note: the quarterly index is calculated as the average over the quarter of the values of the monthly index.

Figure 2.1 Euro area GDP and monthly business cycle indexes (levels), 1988-2002, January 1988=100



Note: shaded areas mark business cycle recessions with absolute declines in economic activity.

Figure 2.2 Euro area GDP and monthly business cycle indexes (growth rates), 1988-2002



Note: shaded areas mark growth rate cycle recessions with decreasing growth rates of economic activity.

In Figures 2.1 and 2.2 recessionary periods are shaded to facilitate visual inspection, but it is informative to look at the differences in turning points in some more detail. Table 2.2 shows the turning points of the indexes in levels (cf. Figure 2.1). These turning points correspond to the turning points of the classical cycle and signal absolute expansions and contractions in economic activity. Table 2.3 shows the turning points for the growth rates of the indexes (cf. Figure 2.2). These turning points signal slowdowns and accelerations in economic growth and correspond to the growth rate cycle. A turning point of the growth rate cycle will generally lead a turning point of the classical cycle since a slowdown in growth usually occurs before growth turns negative. Furthermore, a series generally has more growth rate cycle turning points than classical cycle turning points since absolute declines in economic activity are rarer than slowdowns in growth. This is confirmed by comparing the turning points of GDP in Table 2.2 and Table 2.3. In the period 1988-2002, GDP showed only one classical cycle, but five growth rate cycles. As discussed before, turning points are shown for both monthly and quarterly series, first of all to ensure the chronology is robust to the interpolation method for GDP, but also to check whether it is robust for the different BCIs.

Table 2.2 Business cycle turning points of euro area GDP and business cycle indexes

	Peak and trough dates				*Leads/lags versus EuroGDP*		
	EuroGDP	EuroIJR	EuroTCB	EuroCOIN	EuroIJR	EuroTCB	EuroCOIN
Monthly indexes							
Peak	Mar-92	May-92	May-92	Apr-92	2	2	1
Trough	Mar-93	May-93	Jul-93	Oct-93	2	4	7
Quarterly indexes							
Peak	1992Q1	1992Q2	1992Q2	1992Q1	1	1	0
Trough	1993Q1	1993Q2	1993Q2	1993Q3	1	1	2

Note: positive figures denote a lag of x months

Table 2.3 Growth rate cycle turning points of euro area GDP and business cycle indexes

	Peak and trough dates				*Leads/lags versus EuroGDP*		
	EuroGDP	EuroIJR	EuroTCB	EuroCOIN	EuroIJR	EuroTCB	EuroCOIN
Monthly indexes							
Peaks	Mar-90	Dec-88	Oct-88	Feb-89	-15	-17	-13
	Mar-92		Jan-92		M	-2	M
	Dec-94	Jul-94	Oct-94	Oct-94	-5	-2	-2
	Dec-97	Jul-97	Jun-97	Nov-97	-5	-6	-1
	Sep-99	Oct-99	Sep-99	Nov-99	1	0	2
Trough	Sep-89				M	M	M
	Sep-91		Sep-91		M	0	M
	Mar-93	Nov-92	Jan-93	Nov-92	-4	-2	-4
	Dec-95	Dec-95	Dec-95	Nov-95	0	0	-1
	Dec-98	Aug-98	Nov-98	Oct-98	-4	-1	-2
	Dec-01	Aug-01	Nov-01	Nov-01	-4	-1	-1
Average lead/lag					-4.5	-3.1	-2.8
Average absolute lead/lag					4.8	3.1	3.3
Quarterly indexes							
Peaks	1989Q1	1988Q4	1988Q4	1989Q1	-1	-1	0
	1994Q1	1994Q3	1994Q4	1994Q4	2	3	3
	1997Q2	1997Q3	1997Q2	1997Q4	1	0	2
	1999Q3	1999Q4	1999Q3	1999Q4	1	0	1
Trough	1993Q1	1992Q4	1993Q1	1992Q4	-1	0	-1
	1995Q4	1995Q4	1995Q4	1995Q4	0	0	0
	1998Q4	1998Q3	1998Q4	1998Q4	-1	0	0
Average lead/lag					0.1	0.3	0.7
Average absolute lead/lag					1.0	0.6	1.0

Note: positive figures denote a lag of x months, negative figure a lead of x months, M denotes missed turning points.

Tables 2.2 and Table 2.3 show that none of the three indexes perfectly matches the peaks and troughs of the cycles of GDP. However, the similarity between the turning points of the indexes and those of GDP is considerable. Table 2.2 shows that the euro area had one classical cycle between March 1992 and March 1993. The EuroIJR index had both its peak and trough two months later than GDP. The EuroCOIN index lagged one month at the peak and lagged seven months at the trough. EuroTCB lagged one month at the peak and four months at the trough. The other indexes as well as GDP also showed negative growth in 2001, but the period was too short to signal a turning point. The Bry-Boschan algorithm smoothed these dips and thus did not produce recession signals. The quarterly chronology matches the monthly turning points with generally modest lags.

Table 2.3 shows the turning points of the euro area growth rate cycle and the turning points for (the growth rates of) each of the BCIs. As could already be seen from Figure 2.2, it is much harder for the BCIs to match turning points of the GDP growth rate cycle than those of the classical business cycle. This is partly due to the fact that there are simply more growth rate cycles, but also because the Bry-Boschan algorithm was originally designed to pinpoint classical turning points. As discussed in Section 2.2, the algorithm includes a number of decision rules, such as the minimum period between a peak and a trough and between two peaks or two troughs. These criteria are based on the U.S. classical business cycle chronology as maintained by the NBER Dating Committee and unfortunately, it is not known how appropriate these rules are for dating growth rate cycle turning points.

Some of the difficulties in dating peaks and troughs in growth rate cycles show up when comparing the monthly chronology in the top panel of Table 2.3 with the quarterly chronology in the bottom panel. Based on the monthly series, GDP showed a trough in September 1991 and a peak in March 1992. In the quarterly chronology this upswing was too short to show up as a turning point. Focusing on the monthly chronology in the top panel of Table 2.3, the early 1990s is a period for which turning points are hard to determine. Compared to the other BCIs, EuroTCB performs best with only one missed trough, compared to one missed peak and two missed troughs by the other two BCIs. In the second half of the 1990s, the BCI turning points are in better accordance with the

GDP turning points, although leads of up to six months can be seen. The average absolute lead/lag is slightly larger than one quarter for both EuroTCB and EuroCOIN and nearly five months for EuroIJR.

The bottom panel of Table 2.3 shows that the BCIs perform relatively better in identifying growth rate cycle turning points at a quarterly frequency. As mentioned before, the number of peaks and troughs that were picked out are the same and the average absolute lead or lag is no bigger than one quarter. EuroTCB once again has a very low lead/lag, with EuroIJR and EuroCOIN having an average lead/lag of one quarter.

In summary, the three BCIs pick up the two classical turning points in euro area GDP, but have more difficulties in signalling the growth rate cycle turning points. The performance of the three BCIs is roughly comparable, with a slight advantage for EuroIJR in determining classical turning points and a modest advantage for EuroTCB in identifying growth rate cycle turning points. However, differences in growth rate cycle peaks and troughs between monthly and quarterly series are an indication that further research is warranted.

2.5 Driving Forces of the Euro Area Growth Rate Cycle

One of the main advantages of using only a relatively small dataset to construct a business cycle index is that it makes it easier to analyze the impact of individual series. Although the EuroIJR index includes only variables for a limited number of countries, such an analysis should help to understand some of the dynamics of the euro area growth rate cycle. A first piece of information in this analysis is the weighting matrix, (see equation 2.2). Another useful perspective is given by the average contribution of each variable to the index. The contribution of a variable to the index is given by the weight times the value of the variable in a particular month. Table 2.4 shows these weights and contributions for all variables. The weight and contribution of each variable is calculated by summing across leads and lags. Two columns with average contributions are included, one averaged over all months and another averaged over those months where the value of the index in absolute sense was larger than 0.1 (this was the case in more than 85 percent of the months). The reason for the latter adjustment is that in months with small values of the index, the relative contributions can be quite large.

Table 2.4 shows that euro area GDP is the most important variable in the index, although by no means the only important one. There are also a number of variables with negative weights, meaning that these variables were negatively correlated with euro area GDP over this period. In other words, these variables are countercyclical. As the final two columns show, these variables do make, on average, a positive contribution to the index. Some variables make negative contributions, but this is mostly due to large contribution shares in months where the index is close to zero, because excluding these months nearly eliminates negative contributions.

It is also interesting to see that the contribution of GDP is considerably larger than its weight (around two times as large). Since all variables have been normalised, this finding cannot reflect differences in the relative size of changes in variables. Instead, the reason might be that some variables move more in line with the index as a whole than others, but no useful measure was found to show this. Other important variables are German industrial production (with an average contribution of 11.5 percent), French imports (6.3 percent) and Spanish household consumption (15.3 percent). Quite significant is also the presence of variables with small contributions, such as for example the Spanish order book survey. It would be very useful if statistical criteria could be used to remove such variables from the index since they are likely to mostly add noise to the system.[32]

32 See Boivin and Ng (2003) for criteria to include variables or weight them according to the correlation of the error with other series' errors. This seems a potentially fruitful approach, although the statistical foundations are less clear. For the state of the art on inference for large factor models see Bai (2003).

Table 2.4 Weights and contributions of the EuroIJR index

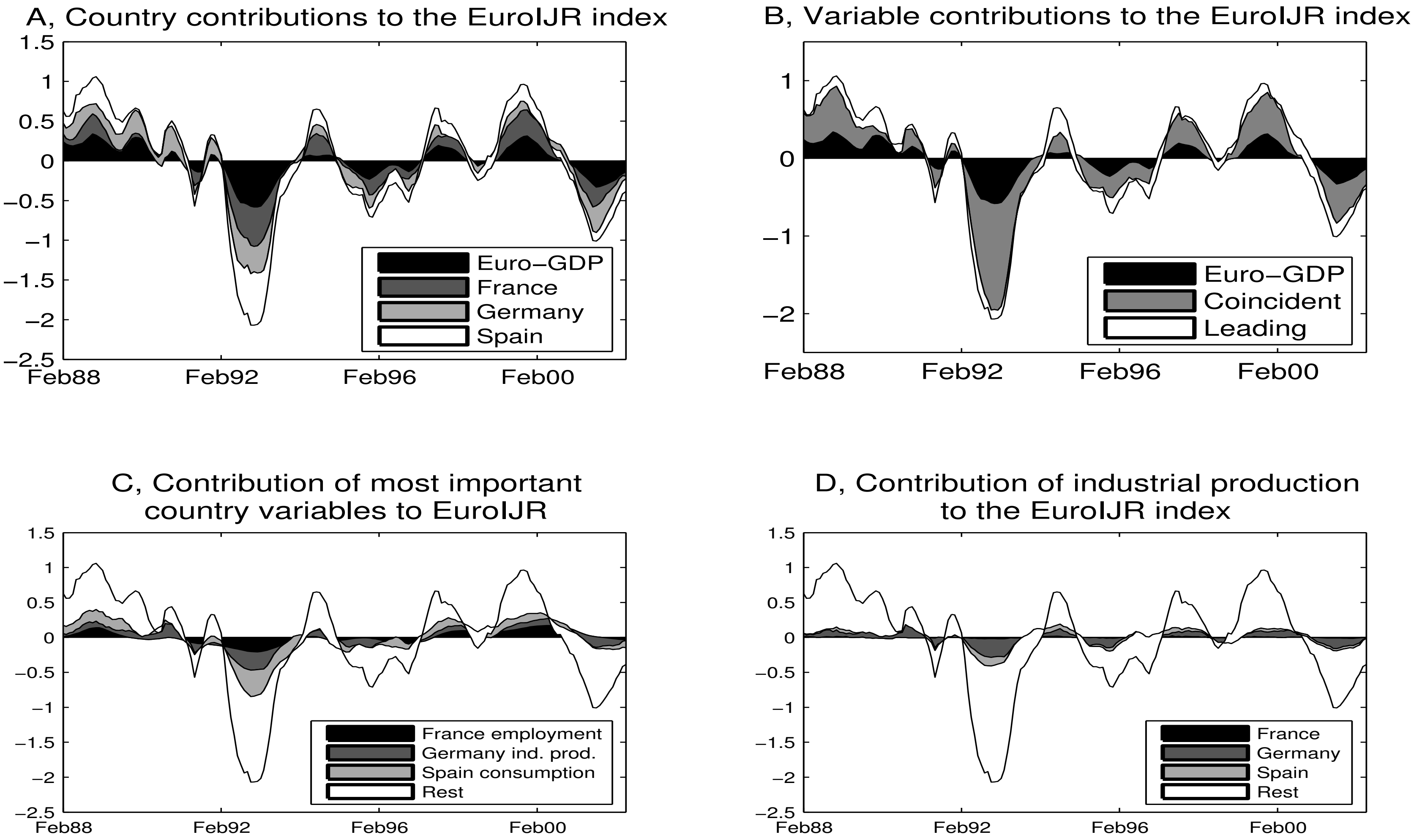
Country	*Type*	*Variable*	*Weights*	*Contribution share*	
				All months	Excl. outliers
France	LEAD	Bond Yield 10 year	4.3	3.7	3.4
France	LEAD	Yield Spread - 10 year minus Day-Day Loan	-3.1	3.2	0.2
France	LEAD	Stock Price SBF 250 Index	-0.1	1.2	0.2
France	LEAD	Personal Consumption of Manuf. Goods	2.9	-3.5	1.1
France	LEAD	Building Permits - Residential	0.4	0.1	0.2
France	LEAD	New Unemployment Claims	-0.3	0.3	0.7
France	LEAD	Industrial New Orders	0.1	-1.2	0.0
France	LEAD	Consumer Confidence Index	1.6	0.4	0.3
France	LEAD	Change in Stocks	4.2	3.8	1.8
France	LEAD	Ratio Deflator of Manuf. Value Added to Unit Labor Cost	2.3	0.6	0.5
France	COIN	Retail sales	2.0	0.1	0.7
France	COIN	Industrial Production	1.8	0.6	0.7
France	COIN	Real Imports	6.3	7.2	6.3
France	COIN	Paid Employment	5.1	-2.9	7.1
Germany	LEAD	New Orders - Investment Goods	0.4	0.7	0.1
Germany	LEAD	Yield Spread - 10 year minus 3 month	2.4	1.2	1.0
Germany	LEAD	New Orders - Consumer Confidence Index	-0.7	0.5	-0.2
Germany	LEAD	Change in Inventories	-2.4	3.0	1.0
Germany	LEAD	New Orders - Residential Construction	5.5	-3.4	1.0
Germany	LEAD	Stock Prices	0.9	1.6	0.3
Germany	LEAD	Gross Enterprise and Property Income	5.7	-1.5	1.6
Germany	LEAD	Growth Rate for Consumer Price Index for Services	-2.1	1.3	0.2
Germany	COIN	Industrial Production	10.3	17.0	11.5
Germany	COIN	Employment - Number of People Employed	0.7	2.0	0.4
Germany	COIN	Manufacturing Sales	4.7	3.6	2.8
Germany	COIN	Retail sales	7.1	10.9	4.1
Spain	LEAD	Construction Component of Industrial Production (3-m ma)	1.1	-0.1	0.4
Spain	LEAD	Capital Equipment Component of Industrial Production (3-m ma, s.a.)	1.6	-0.7	0.2
Spain	LEAD	Spanish Contribution to Euro M2 (s.a.)	2.5	1.8	1.2
Spain	LEAD	Spanish Equity Price Index	-0.7	0.3	-0.1
Spain	LEAD	Long-term Government Bond Yield (Inverted)	-3.0	2.0	1.9
Spain	LEAD	Order Books Survey (3-m ma, s.a.)	0.9	0.0	0.0
Spain	LEAD	Job Placings (3-m mov. av., s.a.)	2.2	0.5	0.3
Spain	COIN	Final Household Consumption (Q)	9.3	9.5	15.3
Spain	COIN	Industrial Production Excluding Construction (3-m ma)	4.1	1.6	2.0
Spain	COIN	Real Imports (3-m ma)	5.3	1.9	2.9
Spain	COIN	Retail Sales Survey (s.a.)	1.4	-0.2	0.1
EuroArea	GDP	Gross Domestic Product (Q)	15.4	32.9	28.7
Total			100.0	100.0	100.0

Source: Indicators: The Conference Board (www.globalindicators.org). Weights and contributions: own calculations.
Notes: COIN: Coincident indicators; LEAD: Leading indicators; Weights: share, summed across leads and lags, calculated from projection matrix. 3-m ma: 3 month moving average. sa: seasonally adjusted. Contribution share: calculated as the share of the changes in each indicator times its weight in the total change of the index. Outliers are defined as month where the EuroIJR index value was less than 0.1 in absolute sense. This cut-off point was chosen because nearly all large contributions (of more than 100% of the index in that month) occured in such months.

To further illuminate the contributions of variables to the index, Figure 2.3 shows a number of plots, where the shaded areas give the contribution by (a set of) variables. Panel A shows how the variables for the different countries, as well as euro area GDP affect the EuroIJR index.[33] This reveals part of the pattern of economic growth in the 1990s. In the early 1990s, most of European growth was driven by Germany with little contribution from France and Spain. The main recession starting around the end of 1991 shows large negative contributions from all three countries, as well as from the overall euro area GDP. Toward the end of the 1990s, France and Spain were making large contributions to positive values of the index, but German variables hardly made any contribution. The relative size of the countries in terms of GDP does not seem to be the most important predictor of their share of the contributions, although this set of countries may simply be too close in relative size to easily distinguish. A more thorough test of this matter would include data for countries such as Finland or Ireland. Finally, the recession starting around 2001 once again features sizable contributions from each of the countries. From this limited set of countries and time span, there seems to be no evidence of idiosyncratic shocks that led to recessions in only one of the countries. This issue is analyzed in more detail in the next chapter.

33 Each of the countries also influences the index indirectly by their contribution to Euro area GDP, but we have not separately distinguished this impact.

Figure 2.3 Contribution to EuroIJR by its components



Panel B shows the contributions from the group of coincident variables and from the set of leading variables. This figure reveals that especially in the recession of 1992-1994 coincident variables played a dominant role. Visual inspection does not reveal important signals from the leading variables, but as noted before, a formal evaluation of the forecasting performance of the index would proceed along different lines. Finally, Panels C and D show the contribution from individual variables to the index. Panel C shows the contribution from the most important variable from each country in terms of its contribution to the total index. These three variables are certainly not driving all movement in the index, as especially the recession in 2001 reveals: after the index had turned negative, it took a number of months before these variables also made a negative contribution. In the recession of the early-1990s, the three variables are more synchronized with the rest of the variables.

It is striking to look at the relative importance of similar variables for different countries. Panel D shows the contribution of industrial production of each country to the EuroIJR index. German industrial production is clearly the most important, even though German manufacturing is only about 30 percent of euro area manufacturing (French and Spanish manufacturing are about 20 and 10 percent of euro area manufacturing, respectively). This difference is confirmed when looking at the weight of each series in Table 2.4. While German industrial production receives a weight of more than 10 percent, French and Spanish industrial production get a weight of 1.8 and 4.1 percent, respectively. This seems to indicate that German manufacturing plays a much more important cyclical role than is indicated by its size. This may be partly due to the greater importance of more cyclical capital equipment manufacturing in Germany, but international linkages may also be important. Once again, however, firm conclusions are hard to come by due to the limited set of countries that is studied.

2.6 Concluding remarks

A timely and up-to-date picture of economic circumstances is invaluable for decision makers in both government and business. Since GDP is only released once a quarter and with a considerable lag, earlier and more frequent indexes of the state of economic activity are useful, especially in turbulent economic times. Such indexes, constructed by statistical analysis, can be a useful complement to models that have to make assumptions about structure of the economy or behaviour by consumers and firms.

This chapter compared the performance of two different methods for constructing business cycle indexes, namely the NBER method and the generalized dynamic factor model. In the NBER method, variables are selected for inclusion in the index based on a researcher's judgment of how closely the cyclical behaviour of a variable matches that of an index of economic activity such as GDP. The generalized dynamic factor model of Forni *et al.* (2000) uses statistical criteria to give a variable a larger or smaller weight.

An advantage of the generalized dynamic factor model compared to the NBER method is that business cycle indexes can be constructed with a smaller number of (judgmental) choices about the components and their weight in the index, since many of those choices are determined by the statistical model. One advantage of the NBER-type indexes is that the business cycle index is constructed from only a limited number of variables. As a result, changes in the index can be more easily traced back to the component or components that drive this change. This allows analysts and users to evaluate which variables have contributed to a recession, say a slowdown in the industrial production or a drop in employment. If the number of components of the index grows too large, this insight is much harder to get.

Using both the NBER method and the generalized dynamic factor model, three business cycle indexes were compared. The first index is based on euro area GDP and the components of the coincident indexes for France, Germany and Spain from The Conference Board, selected according to the NBER method. The second is the euro area index of Altissimo *et al.* (2001), constructed by applying the generalized dynamic factor model to a dataset with nearly 1000 economic variables. The third index is a hybrid index that uses the 37 components of the Conference Board's coincident and leading indexes for France, Germany and Spain as well as euro area GDP and applies the generalized dynamic factor model to weigh and combine these variables into a business cycle index.

One of the most important uses of a business cycle index is to signal peaks and troughs of business cycles. Therefore, the three indexes are compared based on that criterion. Although none of the three indexes perfectly matches the turning points of euro area GDP, all three are reasonably close. The indexes identify the two classical turning points of GDP in the 1990s, but have more difficulties with growth rate cycle turning points. This is at least partly because the Bry-Boschan algorithm that is used for dating cyclical turning points was designed for dating classical cycles, not growth rate cycles. Differences between the monthly and quarterly chronology of growth rate cycle turning points suggests more research into this issue would be useful.

Overall only a limited number of variables is necessary to capture the salient features of the euro area business cycle. Including more variables adds little extra information, but the added noise may make the index harder to identify (Boivin and Ng, 2003). A business cycle index based on a limited number of variables also makes it easier to identify some of the driving forces of the euro area cycle. The analysis of the hybrid EuroIJR index reveals some important differences between the contributions of France, Germany and Spain to the euro area growth rate cycle. Most notably, the same variable from different countries seems to play very different roles. For example, while German industrial production is one of the variables with the largest impact on the euro area cycle, industrial production in France and Spain make only small contributions. This suggests that German industrial production moves more ‘in tune’ with the overall euro area economy. This brings up the issue to what extent a common monetary policy for the euro area is suitable for each of the individual countries. As this question has important implications for the (political) sustainability of the common currency, it is the topic of the next chapter.

Appendix 2.A The Generalized Dynamic Factor Model

In recent years increasingly large datasets on economic time series have become available. However, many of the existing statistical tools were not well suited to analyze such datasets. One of the tools that is frequently used to extract relevant information from large datasets is factor analysis. The basic idea behind factor analysis is that movements in a large number of series are driven by only a limited number of (latent) common shocks.

In factor models, the N series in a dataset with T observations each are decomposed into a common component (χ) that is driven by only $Q<N$ common shocks (u) and an idiosyncratic component (ξ): $x_{it} = \chi_{it} + \xi_{it}$. In the standard static factor model the implicit assumption is made that all series are only contemporaneously affected by the common shocks. The Generalized Dynamic Factor Model (GDFM) of Forni *et al.* (2000) is both dynamic and it allows for limited cross-correlation between the idiosyncratic components. For most time series analysis the dynamic character of the model is especially important as common shocks may not have an impact on a series contemporaneously but with a lead or lag. The GDFM allows for a decomposition of the common component in a cyclical χ^C and non-cyclical χ^{NC} component so the complete decomposition becomes:

(A2.1) $$x_{it} = \chi_{it} + \xi_{it} = \chi_{it}^C + \chi_{it}^{NC} + \xi_{it}.$$

The generalized dynamic factor model proposed by Forni *et al.* (2000) can be written as:

(A2.2) $$\boldsymbol{X} = \boldsymbol{U}\boldsymbol{B}^C(L) + \boldsymbol{U}\boldsymbol{B}^{NC}(L) + \boldsymbol{\Xi},$$

which is the matrix notation of Equation (2.1). Uppercase characters denote the matrix of corresponding lowercase variables. The series x_{it} are normalized to have a mean of zero and a variance of one.

The factor loadings b and common shocks u are not uniquely identifiable, but Forni *et al.* (2000) prove that under four assumptions the common component of each series can be uniquely identified and consistently estimated as both N and T go to infinity. First of all, the common shocks are white noise and the idiosyncratic components are stationary processes, uncorrelated with past, present and future values of the common shocks. Second, the spectral density matrix of the observation matrix $\boldsymbol{X}$ exists. Third, the first Q eigenvalues go to infinity as the number of series N goes to infinity and finally, all remaining eigenvalues remain bounded.

The proposed estimation scheme consists of four steps. In the first step, the information in the time domain is transformed to the frequency domain, to easily incorporate information of leading and lagging relationships. Second, a filter is constructed that maximizes the variance explained by the common component using principal component analysis. Third, the filter is transformed back to the time domain and fourth, applied to the time series to obtain the common component of each series.

More precisely, the estimation scheme is as follows. The first step is to calculate a series of auto-covariance matrices of the data matrix $\boldsymbol{\Gamma}_m$, $m = -M, ..., M$. The integer M represents the number of leading and lagging observations that contain information on the current common component. To obtain a consistent estimator, M must go to infinity and the quotient M/T must go to zero as T tends to infinity. Forni *et al.* (2000) propose to use $M = round(2/3)T^{1/3}$. The second step is to use a Fourier transformation on the auto-covariance matrices to estimate the spectral density using the Bartlett kernel estimator:

(A2.3) $$\boldsymbol{\Sigma}(\theta_t) = \sum_{m=-M}^{M} \boldsymbol{\Gamma}_m \omega_m e^{-im\theta_t} \ , \ t = 0,1,...,F ,$$

with $\omega_m = 1 - [|m|/(2M+1)]$ the Bartlett kernel. This means the spectrum, $\Sigma(\theta_t)$, is evaluated at some predetermined number of frequencies, F, given by $\theta_t = 2\pi t/(F+1)$.

In the third step the Q largest (real) eigenvalues are calculated as well as the corresponding (complex) eigenvectors $p_q(\theta_t)$ of the spectral density matrix at frequency θ_t. If we stack the eigenvectors in a matrix $\boldsymbol{V}(\theta) = [p_1(\theta),..., p_Q(\theta)]$, the weights of the filter in the frequency domain are given by:

(A2.4) $$\boldsymbol{K}(\theta_m) = V(\theta_m)V(\theta_m)', \ m = -M,...,M ,$$

with V' the transposed complex conjugate of V.

To select only the cyclical part of the common component, the inverse Fourier transform is applied in the third step using only the frequencies associated with the cyclical frequencies and obtain the two-sided filter:

(A2.5) $$\boldsymbol{K}_k^C = \sum_m \boldsymbol{K}(\theta_m) e^{ik\theta_m}\ ,\ k = -M, \ldots, M\ ,$$

with m in the summation such that $|\theta_m| < (2/14)\pi$, so θ_m is part of the cyclical interval. The final step involves applying the filter to the dataset $\boldsymbol{X} = (x_{it}, \ldots, x_{Nt})$ for all $t = 1, \ldots T$, to get an estimator of the cyclical common component:

(A2.6) $$\hat{\boldsymbol{\Phi}}^C = \frac{1}{2M+1} \sum_{k=-M}^{M} L^k(\boldsymbol{X}) \boldsymbol{K}_k^C\ .$$

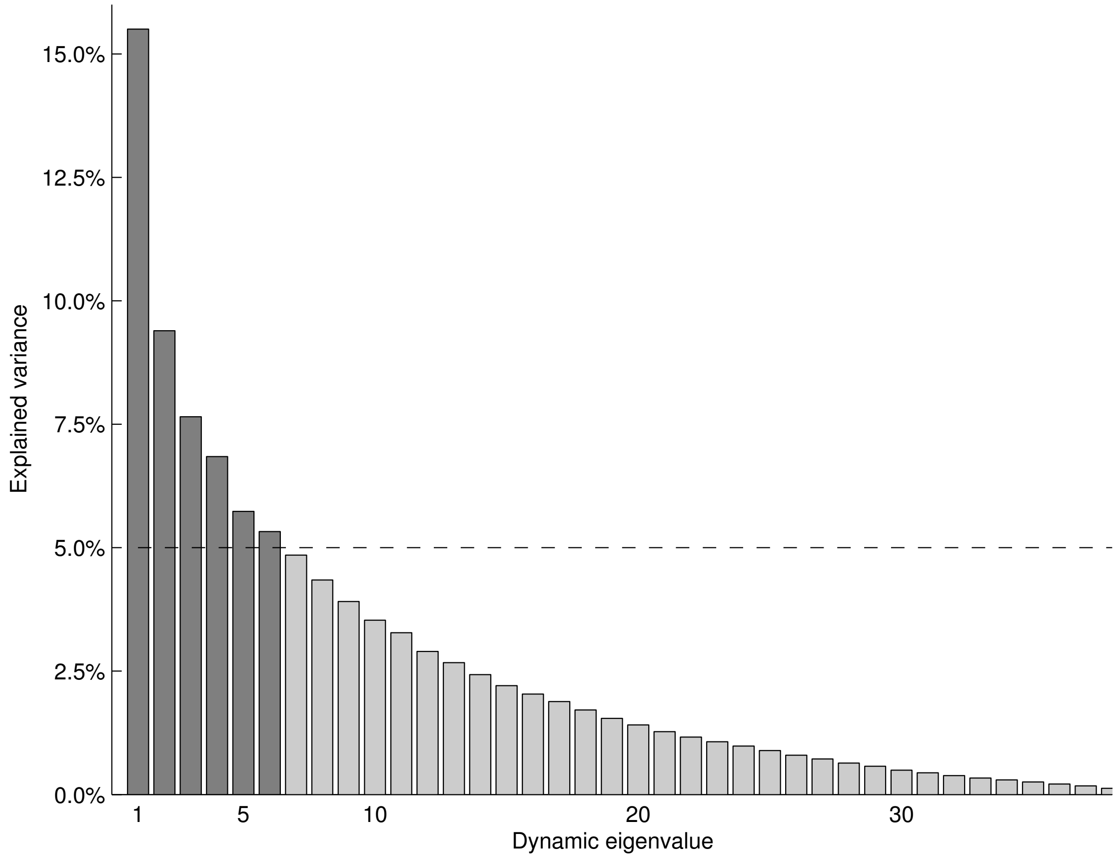
That is, each common component is a moving average (M lags and leads) of the series in question. The weights of this moving average are determined by the eigenvectors of the spectral densities. For M =0 this model reduces to the standard static principal component model.

Choice of *Q*

Until now the number of common shocks Q was assumed to be known. In practice of course, Q must be chosen or ideally be estimated based on the dataset at hand. As Forni *et al.* (2000) point out, there is no formal statistical test to help identify the number of factors in their GDFM. However, Forni *et al.* (2000) propose to relate the choice of Q to the variance explained by the i^{th} eigenvalue (averaged over all frequencies). If the model assumptions are fulfilled, there is a substantial gap between the variance explained by the Q^{th} and the $(Q+1)^{th}$ eigenvalue. Forni *et al.* (2000) propose to include factors as long as they explain 5 percent of total variance and this rule of thumb is followed here.

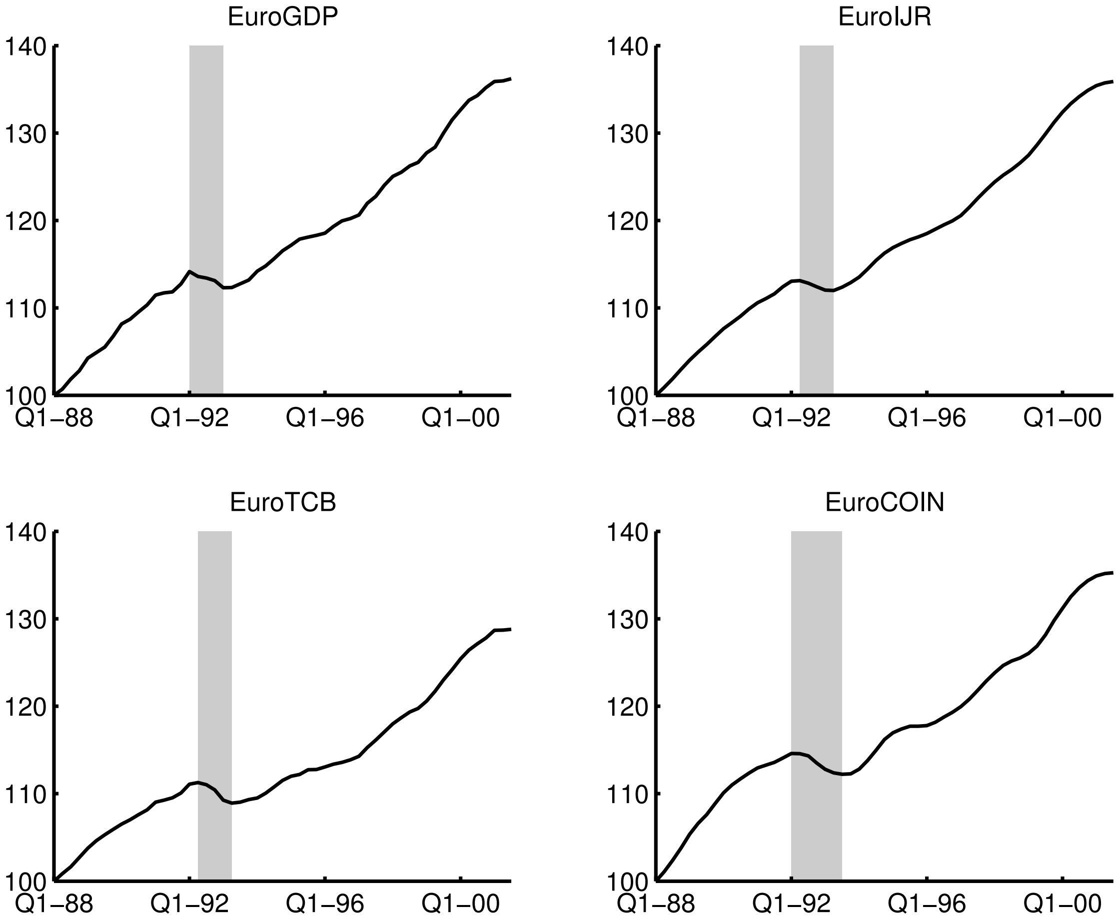
Appendix Figure 2.1 shows the percentage of total variance explained by the different eigenvalues. As the figure shows, only the first 6 eigenvalues explain more than 5 percent, so Q=6 is chosen. The figure also shows that the choice of Q=6 is somewhat arbitrary, as the difference in explained variance with eigenvalues 7 and 8 is quite small. Some robustness analysis, however, suggests that the resulting business cycle index is not very sensitive to the exact choice of Q.

Appendix Figure 2.1 Percentage of variance explained by each eigenvalue (38 series, 189 observations)



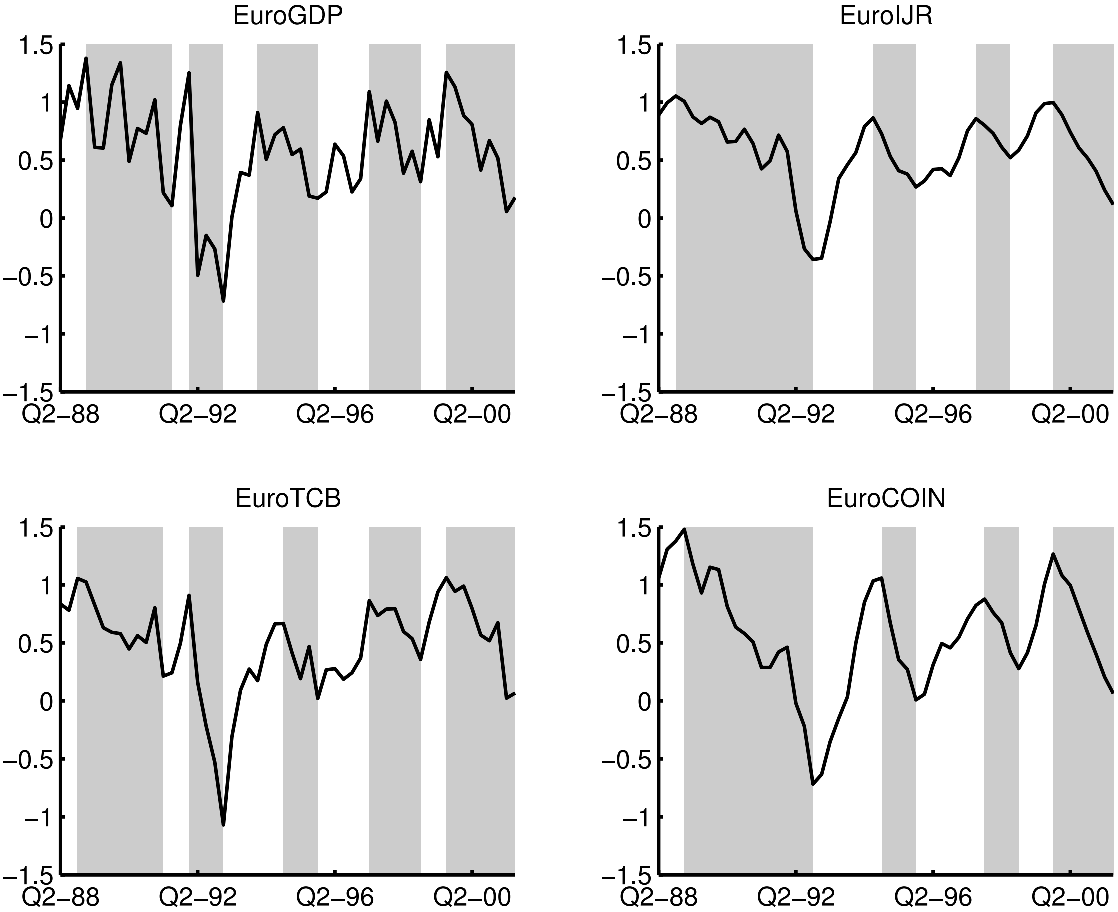
Appendix 2.B Plots of Quarterly GDP and Business Cycle Indexes

Appendix Figure 2.2 Euro GDP and quarterly business cycle index levels, 1988-2002, January 1988=100



Note: shaded areas mark business cycle recessions with absolute declines in economic activity.

Appendix Figure 2.3 Euro GDP and quarterly business cycle index growth rates, 1988-2002



Note: shaded areas mark growth rate cycle recessions with decreasing growth rates of economic activity.

Chapter 3 Business cycle synchronization[34]

3.1 Introduction

One of the main determinants of the success of the European monetary union will be whether the common monetary policy set by the European Central Bank (ECB) is suitable for all member countries. This suitability in turn depends on the degree to which business cycles are synchronized across countries. In setting monetary policy, the ECB can only respond to the average level of economic activity, which can lead to economic and political difficulties for countries that are performing better than the average, but especially, for those that perform worse than the average. The original literature on optimal currency areas (OCAs) argued that if countries are prone to asymmetric shocks, their economies should be flexible enough to absorb these shocks. Mundell (1961) argued that labour migration could be such an absorption mechanism but labour mobility is still less than perfect in Europe.

As a result, research in recent years has examined whether economic and monetary integration will make asymmetric shocks more or less likely. Krugman (1991) argued that with increasing economic integration, specialization would lead to a regional concentration of industries due to agglomeration benefits. In that case, industry-specific shocks will affect some countries more strongly than others. In contrast, the European Commission has argued that more economic and monetary integration will lead to more synchronous business cycles (Emerson *et al.*, 1992), due to, for example, more similar monetary and fiscal policies.

With the increased interest in the determinants of business cycles synchronization, there has also been a growing literature on the measurement of synchronization. Before presenting new empirical results, this chapter starts off by giving an overview of this

[34] This chapter builds on Inklaar and de Haan (2001), de Haan, Inklaar and Sleijpen (2002), de Haan, Inklaar and Jong-A-Pin (2005) and Inklaar, Jong-A-Pin and de Haan (2005). See the acknowledgements for further details.

literature. Part of the overview deals with what types of data have been used, but most attention is devoted to discussing measures of business cycles and synchronization.

To gauge the prospects of Europe's common currency, an obvious starting point is to see whether monetary integration in itself contributes to more similar cycles. Specifically, since the breakdown of the Bretton-Woods system of fixed exchange rates in the early 1970s, there has been a trend towards greater monetary integration within Europe, starting with the Exchange Rate Mechanism (ERM) in 1979 and culminating in the introduction of the euro in 1999. If monetary integration is a dominant determinant of synchronization one would expect the cycles of European countries to have become more similar with no similar development amongst other countries. This issue is taken up in Section 3.2.

To examine the impact of increased economic integration, the United States provides a useful test case. The U.S. has been a monetary union for a long time. Therefore, trends in business cycle synchronization among U.S. states can be revealing about how similar cycles are within a monetary union over time and as a result, it can give some indication of Europe's prospects (Section 3.3).[35]

Up to this point, the discussion about economic and monetary integration has been relatively abstract, while in practice it is a multi-faceted concept reflecting similarities in economic policies, structural features and closeness of trade links. To draw conclusions that are relevant for policy, these different dimensions should be disentangled and their relative importance for business cycle synchronization evaluated. In their seminal paper, Frankel and Rose (1998) show that countries with more intensive trade links have more similar business cycles. Since then, this topic has received increasing attention and a large number of potential determinants has been considered and tested. Section 4 of this chapter analyzes a large set of such variables. The goal is to come up with a robust set of explanatory variables and estimate how monetary union will affect synchronization in Europe.

[35] This is no strict comparison since the period before the U.S. became a monetary union is not analyzed. As a result, differences in the U.S. economic structure relative to the euro area can lead to differences in the eventual synchronization patterns. For example, the greater degree of labour mobility between U.S. states could be an important determinant of synchronization. Despite this, the U.S. experience should still be informative.

The main findings of these analyses are that there is no clear trend in synchronization over time, neither in Europe nor in the United States. This stands in contrast to some earlier studies for Europe, notably Artis and Zhang (1997, 1999), who conclude that a European business cycle is emerging over time. More recently though, research by, e.g. Massman and Mitchell (2004) has shown that periods of greater and lesser synchronization alternate. The U.S. experience is also revealing as it has been a monetary union throughout the period. Indeed, Clark and van Wincoop (2001) established that there is a greater degree of synchronization within the U.S. than within Europe, and this finding is confirmed. Again however, synchronization tends to fluctuate over time. Some economic episodes are shared by nearly all states, such as the Great Depression of the 1930s or the effects of the oil crises of the 1970s but there are also periods of wide divergence in the economic experience of U.S. states. A recent study by Partridge and Rickman (2005) shows that a decline in synchronization among U.S. states in recent decades can be traced to a decline in the volatility of the aggregate U.S. cycle. However, other U.S. research by Kim (1995) shows that specialization across U.S. regions has decreased in recent periods due to more mobile production factors, which presumably has had a positive impact on business cycle co-movement.

The analysis of the determinants of synchronization has more encouraging news for euro enthusiasts. Not only trade intensity, but the similarity of monetary and fiscal policies, the degree of financial integration and the similarity of trade also has a robust positive effect on synchronization and the impact of each of these factors is at least as large as that of trade intensity. Scenarios show that under monetary union these factors will contribute to a greater degree of synchronization. Caution is in order though, as even the most optimistic projections show less than perfect synchronization and there are important uncertainties regarding the similarity of fiscal policy and changes in specialization patterns in the future. This suggests that a reform agenda focusing on flexibility and mobility of production factors is still important and might even stimulate further synchronization due to decreasing specialization.

3.2 Measuring business cycle synchronization

Various studies have looked at the issue of synchronization of business cycles in the euro area, often reaching very different conclusions. Part of these differences can be related to differences in variables used, diverging business cycle measures and methods to assess synchronization. This section therefore deals in turn with the different economic variables that have been considered in previous studies, the differences in the measurement of relevant cyclical information, and different measures of cyclical synchronization.

Data

One obvious reason for differences between studies on business cycle synchronicity is different data sources. The two most important sources are quarterly data on GDP and monthly data on industrial production. In addition, GDP is sometimes decomposed into expenditure categories such as consumption and investment.[36] Annual data is usually avoided to capture more of the high-frequency fluctuations.

Studies of business cycle synchronization should focus on the broadest possible output variable, GDP. In addition, expenditure components can provide further useful information. If, for example, consumption is highly synchronized across countries but government expenditure is not, then one can hypothesize that a large degree of risk sharing between consumers is already taking place, but that fiscal policies are very different. Similarly, correlations between consumption in country A and exports in country B can elucidate the importance of trade links between country A and B.

The conceptual reasoning behind using industrial production is less convincing. First of all, manufacturing activity represents less than 20 percent of aggregate output in the euro zone so a priori it would not seem to be representative of total output. Second, manufacturing output is much more volatile than aggregate output, so the claim to being representative seems even less credible.[37] One could argue that movements in the manufacturing sector are likely to have a more than proportionate impact on GDP since

[36] Some studies, like Angeloni and Dedola (1999), not only look at common output cycles, but also study cyclical movements in consumer prices or stock prices. As the main topic is the level of economic activity, price cycles are not treated here.

[37] Using annual data on value added growth from the GGDC 60-industry database, it can be shown that the standard deviation of annual output growth in the manufacturing sector is more than twice as large as the standard deviation of GDP growth for the euro zone over the period 1979-2003.

sectors such as transport and trade earn their revenues from transporting and trading manufactured goods.[38] Furthermore, the higher frequency at which industrial production data is available, as well as the longer time series is appealing. Still, analysis based on more comprehensive output measures seems preferable to using industrial production.

Measuring business cycles

As discussed in Section 2.2, an important distinction that has to be made is between classical business cycles and growth (or deviation) cycles. In the work by Burns and Mitchell (1946), (classical) business cycles are defined in terms of absolute expansions and contractions of economic activity. Many of the more recent studies, however, look at deviation cycles, or the deviation of economic activity from a 'trend'.

Harding and Pagan (2002, 2005) discuss some of the arguments for both cycle concepts, concluding that the classical cycle should be the relevant measure to be explained by researchers. First, classical cycles are less subjective since no trend has to be identified and second, policymakers are more interested in recessions instead of slowdowns relative to a trend. There is a relationship between classical and deviation cycles since slowdowns generally precede a recession but not every slowdown leads to a recession. However, a practical reason why most researchers focus on deviation cycles is that most (parametric) measures used to describe the cycle need stationary series as input.

Most studies in this literature focus on growth cycles in European countries and a variety of filtering techniques is used to separate trend and cycle. This makes it useful to describe the salient features of these techniques.[39] The most straightforward filtering technique is calculating first differences.[40] Usually, this is sufficient to render the series of interest stationary.[41] However, as, for example, Baxter and King (1999) point out, first differencing does remove a trend from a series, but at the cost of a shift in the peaks and

[38] Indeed, the correlation between manufacturing output growth and GDP growth from the GGDC 60-industry database is 0.9 for the euro zone over the period 1979-2003.
[39] See also, for example, Canova (1998), Zarnowitz and Ozyildirim (2002), and Massmann and Mitchell (2004) for an overview of various filtering methods.
[40] If the original series is expressed in natural logs, first differencing yields growth rates. Various studies employ growth rates (e.g. Frankel and Rose, 1998, Otto *et al*., 2001 and Kose *et al*., 2003).
[41] In other words, the moments (mean, variance, etc.) of the series do not depend on time.

troughs of the differenced series and a larger volatility.[42] The phase shift may not be too important when comparing cycles across countries since this phase shift is the same for both countries. However, the larger weight on higher frequencies in the series emphasizes the irregular ‘noise’ over the cyclical movements.

Canova (1998) and Massmann and Mitchell (2004) discuss a number of parametric methods such as the Beveridge-Nelson decomposition, unobserved component models and simple linear time trends. Since such methods are hardly used in the literature on business cycle synchronization, these will not be discussed in depth. Most studies apply non-parametric filters such as the Hodrick-Prescott (HP, 1997) filter; the Baxter-King (BK, 1999) and Christiano-Fitzgerald (CF, 2003) band pass filters and the phase average trend (PAT, Boschan and Ebanks, 1978).

In general, filters can be viewed as weighted moving averages. For example, first differencing can be interpreted as applying a filter with a weight of one on the current observation and a weight of minus one on the previous observation. Usually, the filters are two-sided, which means that the current value of the trend depends on both past and future values of the series under observation. The use of a two-sided, symmetric filter ensures that there is no phase shift between the original and the filtered series.[43] However, as a result, the trend value near the beginning and end of the sample will be less reliable since part of the moving average cannot be calculated. Quite often this problem is ignored, although the standard programs to calculate the BK filter automatically remove a certain number of observations at the start and end of the series. Another alternative is to forecast and backcast the original series using, for example, an AR process.

Probably the most widely used filter is the Hodrick-Prescott filter. This filter estimates the trend component by minimizing deviations from trend, subject to a predetermined smoothness of the resulting trend:

[42] In other words, first differencing induces a phase shift and puts a larger weight on higher frequencies of the time series.
[43] See, for instance, Baxter and King (1999).

(3.1) $$\min_{y_t^{tr}} \sum_{t=1}^{T} \left(y_t - y_t^{tr}\right)^2 + \lambda \sum_{t=2}^{T} \left(\left(y_{t+1}^{tr} - y_t^{tr}\right) - \left(y_t^{tr} - y_{t-1}^{tr}\right)\right)^2 .$$

In this equation y_t is the original series, y_t^{tr} the estimated trend and λ is the smoothness parameter. Note that this is a two-sided filter in that the current deviation from trend is minimized, subject to the change in the trend from the current period to the next and the change from the previous period to the current. Note also that if λ is set to zero, the 'trend' will simply follow the original series, while if λ is set to infinity, a linear time trend will be estimated.

For quarterly data, Hodrick and Prescott (1997) argue that a standard deviation of the cyclical component of 5 percent is moderately large, just as an 1/8th of a percent standard deviation of the quarterly trend growth rate. Based on these priors, they set λ to 1600 for quarterly frequencies on the assumption that trend and cycle are identically and independently distributed.[44] The problem of choosing appropriate smoothness parameters for data at frequencies other than quarterly has in the past mostly been solved by keeping the 5 percent variability in the cyclical component fixed and scaling the variability of the trend component up or down. So the appropriate λ for annual data becomes 100 and for monthly data 14,400.[45] However, using frequency-domain techniques, Ravn and Uhlig (2002) have shown that the same amount of smoothing is achieved by scaling the quarterly lambda by one over the frequency change to the fourth power. So for annual data, λ becomes $(1/4^4)*1600=6.25$.

As noted before, the HP filter can be viewed as a moving average filter. Specifically, as pointed out by Prescott (1986), the HP filter can be interpreted as a high-pass filter that removes fluctuations with a frequency of more than 32 quarters or 8 years and puts those fluctuations in the trend. Baxter and King (1999) argue that the combination of such a high-pass filter on the one hand and a low-pass filter (which removes high frequencies) on the other is another improvement since the HP filter still leaves much of the high-frequency noise as part of the cycle.[46] The resulting cyclical

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[44] The calculation is $\lambda = \left(5/0.125\right)^2$.

[45] Calculated as $(5/0.5)^2$ and $(5/0.0417)^2$, respectively.

[46] Zarnowitz and Ozyildirim (2002) argue that such high-frequency fluctuations are important to determine the exact date of a business cycle peak or trough. This consideration does not seem to be too important for measuring cycle synchronization, though.

component does not contain any fluctuations with high or low frequencies beyond predetermined cut-off points, and this defines a band pass filter. Baxter and King (1999) and Christiano and Fitzgerald (2003) derive approximate band pass filters, using somewhat different assumptions.[47] Although different in details, in both cases the weights for the filter are estimated using frequency domain arguments, but the standard Baxter and King (1999) filter is two-sided, while Christiano and Fitzgerald (2003) advocate a one-sided filter. Christiano and Fitzgerald (2003) also point out though that both filters are quantitatively similar when looking at cyclical statistics.

Baxter and King (1999) suggest using a band pass filter isolating frequencies between 6 and 32 quarters, based on the observation in Burns and Mitchell (1946) that business cycles are generally confined to these frequencies. The analogy is somewhat problematic, however, as the 6 to 32 quarter interval refers to classical cycles, not to growth cycles. Economic variables generally trend upwards, so classical cycles between 6 and 32 quarters will conform to a smaller frequency band for growth cycles (Zarnowitz and Ozyildirim, 2002).

Finally, the Phase Average Trend (PAT) is closely related to the method used to calculate business cycle turning points. The PAT filter, originally proposed by Boschan and Ebanks (1978) and more recently described in Zarnowitz and Ozyildirim (2002), starts off by estimating a 25-quarter moving average. The turning points of the deviations from this trend are dated using the Bry and Boschan (1971) algorithm, which generates classical cycle turning points that closely approximate those selected by the NBER Business Cycle Dating Committee. Finally, the trend is estimated by connecting the mean values between each cyclical peak. Although the OECD uses this filter for their business cycle indicators, not many studies apply this filter. However, Zarnowitz and Ozyildirim (2002) show that the PAT filter gives similar turning points as other filters such as the HP and the BK band pass filter. Artis and Zhang (1997) and Calderon *et al.* (2002) also conclude that the choice of filtering method is not crucial for their conclusions. Massmann and Mitchell (2004, p. 303), who consider the largest number of filtering methods, conclude that "our examination of convergence between euro area business

[47] An ideal band pass filter would need a time series of infinite length, so an approximation is always necessary.

cycles indicates that there are substantive similarities across alternative measures of the business cycle." This finding is remarkable since Canova (1998) concluded that different cycle filtering methods lead to different conclusions regarding business cycle facts in the U.S. These findings are not mutually exclusive, since Canova compares different filters within a country, while Massmann and Mitchell and others compare the results from different filters across countries. So although the various filters may indeed "extract different types of information" (Canova 1998, p. 475), the findings are similar when comparing this information across countries.

In summary, studies that use standard filters such as the HP, BK and CF filters are likely to yield similar results as long as the same data are used. These three filters also perform reasonably well in isolating fluctuations in the data of certain frequencies, which after all is the most important goal of filtering. Using first differences is likely to lead to larger problems, as it puts too much weight on high-frequency fluctuations.

A quite different approach to extracting cyclical information is by estimating Markov switching models. These models, first used in this setting by Hamilton (1989) allow the economy to 'switch' between expansions and recessions. The probability of being in recession can then be compared across countries to gauge the commonality of business cycles across countries. This methodology is relatively less established for comparing business cycles across countries, but Artis, Krolzig and Torro (2004) implement this method in a recent study.

Another comparatively new method is the one proposed by den Haan (2000). His approach to analyzing the co-movement between series is to study the forecast errors from a VAR that includes (at least) the two series of interest. This way, the dynamics and possible cointegration of the series can be taken into account. Up until now, only Camacho *et al.* (2005) have used this method.

Synchronization measures

Given a certain measure of the cycle, the important question arises to what extent these cycles move together across countries. Most studies use simple (Pearsson) correlation coefficients of the cyclical part of GDP to answer this question, but other measures have been suggested in the literature as well, like the dynamic correlation measure of Croux, Forni and Reichlin (2001), the phase-adjusted correlation of Koopman and Azevedo (2003) and the concordance index of Harding and Pagan (2002).[48]

The measures suggested by Croux *et al.* (2001), Koopman and Azevedo (2003) and Harding and Pagan (2002) require some more discussion. The dynamic correlation measure of Croux *et al.* (2001) is defined as the co-spectrum between two series over the product of the spectra of each series. The authors then go on to define this measure over a certain frequency band, i.e. fluctuations in the series with a certain period. They show that for time series with an infinite number of observations, the dynamic correlation between two series over a frequency band is equal to the regular correlation between two band pass filtered series. For finite time series this equality does not hold in general as both the band pass filter and the dynamic correlation are estimated imperfectly. Despite this, it is likely that the two measures will be quite close in practice. Croux *et al.* (2001) suggest that for more than two series, one should look at the cohesion of these series. The authors define cohesion as the (weighted) average of the binary dynamic correlation coefficients. This measure provides a useful summary statistic on the degree of co-movement within a group of countries by avoiding the problem of choosing a base country. Still, the full distribution of correlation coefficients as for example plotted in Massmann and Mitchell (2004) provides even more useful information.[49]

Koopman and Azevedo (2003) estimate an unobserved components model that accounts for time-varying phase differences as well as a time-varying relation between cycles. Although unobserved components models can also be used to distinguish trend and cycle, Koopman and Azevedo (2003) take band pass filtered series as input. Their method refines standard contemporaneous correlations between cyclical components in two ways, first by separating the contemporaneous correlation into a part due to differences in the position on the cycle of two countries (phase shift) and a 'phase-shift'

[48] Belo (2001) also applies Spearman rank correlations. Camacho *et al.* (2005) use the simple average of various measures (including those of Forni *et al.* (2001), Harding and Pagan (2002) and den Haan (2000)), yielding what they call a comprehensive measure of distance.

[49] More recently, Hughes Hallett and Richter (2004) discuss a measure of business cycle coherence that is similar in spirit to the dynamic correlation of Croux *et al.* (2001). The main innovation is that Hughes Hallett and Richter (2004) allow for time variation in their estimated spectra. This not only allows them to judge how strongly two countries co-move at a certain frequency, but also how this degree of co-movement changes over time. The drawback is that it is as yet hard to gauge how statistically important some of these changes are.

adjusted correlation. Second, they allow for time variation in both the phase shift and the phase-shift adjusted correlation. Although this last innovation seems valuable, they can only practically implement their method by imposing a monotone time function. In other words, the correlation can either go up over the sample period, or it can go down. While this provides useful information, visual inspection of their cyclical component series suggests that periods of stronger and weaker correlation alternate. Furthermore, the finding that the correlation between the cyclical components of each country versus the euro area is around 0.90 near the year 2000 seems puzzling when compared to the results using other methods in studies like Massman and Mitchell (2004), or the estimates presented in the next section.

The concordance index proposed by Harding and Pagan (2002) is a non-parametric co-movement measure that uses a binary indicator variable of recessions and expansions. Referring to this indicator variable for country *x* at time *t* as S_{xt}, the concordance index is defined as:

(3.2) $$I_{x,y} = \frac{1}{T}\left(\sum_{t=1}^{T} S_{xt} S_{yt} + \sum_{t=1}^{T} (1 - S_{xt})(1 - S_{yt}) \right).$$

Put differently, this index measure the percentage of the time where the two series are in the same state. The index is in some ways more flexible than the correlation coefficient since any method for distinguishing between recessions and expansions can be chosen. While the correlation between series of GDP levels will in general be spurious due to the strong trend in those series, classical recessions can be dated from these level series and the concordance index can be calculated. A drawback is that analyzing a binary variable throws away potentially useful information. Still, the concordance index can be a useful complement to correlation measures between detrended series as well as providing a useful measure to analyze classical cycles. Artis, Marcellino and Proietti (2002) provide a related perspective by looking at diffusion indexes. Such a diffusion index for say the euro area, measures the share of countries that are in a recession if the euro area as a whole is in recession. Such indexes can also be modified to measure the share of above-trend countries or countries with positive growth. While the concordance index seems useful to summarize bilateral co-movement between two series, diffusion indexes can provide insight in the co-movement within an aggregate at each point in time.[50]

Most co-movement measures are judged by their characteristics and not so much by economic reasoning. An exception is the work by Kalemli-Ozcan, Sørensen and Yosha (2001), who compare utility under autarky, where the consumption possibilities are constrained by the country's own GDP, and utility under full cross-country risk sharing. In the latter case, consumption possibilities are equal to a fraction of total GDP in the area in which risk sharing takes place.[51] Moving from autarky to full risk-sharing will generally bring utility gains and Kalemli-Ozcan *et al.* (2001) derive the following measure for these gains when assuming log-utility:[52]

$$(3.3) \qquad G^i = \frac{1}{\delta}\left(\frac{1}{2}\sigma^2 + \frac{1}{2}\sigma_i^2 - \text{cov}^i\right),$$

where δ is the intertemporal discount rate, σ^2 is the variance of output growth in the entire economic area, excluding country *i*, σ_i^2 is the variance of output growth in country *i* and cov^i is the covariance between output growth in country *i* and the rest of the economic area. This measure states that the gains from risk-sharing for country *i* will be larger when the standard deviation of GDP growth in country *i* is higher, when the standard deviation of GDP growth in the rest of the risk-sharing area is larger and when the covariance between country *i* and the rest of the area is smaller. The interpretation of this negative sign on the covariance is straightforward as joining an area with largely unrelated fluctuations will provide more insurance by stabilizing aggregate output. Furthermore, the higher the standard deviations of growth, the more is gained by sharing risk.

This measure also focuses attention on an issue that is often ignored when looking at business cycle synchronization. Asynchronous business cycles are assumed to be costly for a monetary union since the common monetary policy will not fit all countries. However, as the analysis by Kalemli-Ozcan *et al.* (2001) makes explicit, transfers of

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[50] Note that diffusion indexes are also used widely in the study of business cycles within a country, amongst others by The Conference Board for the U.S. Leading Index.

[51] In the first case consumption possibilities are equal to GDP_i, and in the second case they are equal to a (long-run) share of total GDP in the currency area.

[52] The authors also consider a constant relative risk aversion (CRRA) functional form for utility. The resulting expression for risk-sharing gains is more complicated, but the intuition is similar.

income across countries could increase aggregate utility and more so with asynchronous business cycles.[53] Interestingly, equation (3.3) bears close resemblance to the correlation coefficients that are often used in the study of business cycle synchronicity since the standard deviations of the two series and the covariance between the series are the main components of both equation (3.3) and of the standard correlation coefficient.

A related problem is how to judge the change in co-movement between cycles over time. The simplest solution is to compare correlations in two periods, for example, before and after the establishment of the ERM (Artis and Zhang, 1997, 1999), or for multiple periods as in Inklaar and de Haan (2001). A more general and less arbitrary approach is to use rolling windows as in Massmann and Mitchell (2004).

Summing up, depending on the purpose, many different methods can be used to measure the amount of co-movement between two countries. In the introduction it has already been spelled out that the main issue is to see whether business cycles in the euro area are similar enough to justify a common monetary policy, whether the similarity has increased over time and which factors can help predict the similarity in the future. Indeed, the simplicity of the correlation coefficient is one its strongest advantages: the main question of interest is whether monetary policy will be suited to a currency area at a point in time. Decomposing co-movement into in-phase and out-of-phase components as in Koopman and Azevedo (2003) may provide interesting information, but it is not very useful from the point of view of the suitability of a common monetary policy.

3.3 Synchronization trends in OECD countries

Although the previous section demonstrated that there are many ways to analyze the co-movement of economic activity across countries, for the empirical analysis it makes sense to consider a more manageable set of indicators. The most commonly used indicator is the correlation coefficient between detrended measures of economic activity. The choice of detrending method is generally not crucial for the results, so here the Baxter-King band pass filter is used.[54] Following the discussion in the previous section

[53] This obviously abstracts from political considerations that could hamper the adoption and operation of such a risk-sharing scheme.

[54] Following Baxter and King (1999), cyclical frequencies are defined as fluctuations between 6 and 32 quarters.

about selecting a measure of economic activity, there is a clear trade-off between GDP and the index of industrial production (IIP) in terms of the scope of coverage and the frequency and length of the time series. Therefore, results based on both measures will be presented.

As the ECB takes the business cycle of the euro area into account when making monetary policy decisions, the most obvious first question is how similar the business cycles of euro area countries are to the aggregate euro area cycle. The analysis is performed using data on quarterly GDP and monthly industrial production for 21 OECD countries between 1970 and 2003, including all euro area countries except Luxembourg.[55] Most of the GDP series are directly from the OECD *Quarterly National Accounts*. These data were supplemented with series from Eurostat and national statistical offices to get the maximum number of observations.[56] The source of the industrial production data is the OECD *Main Economic Indicators* publication. Chapter 1 already showed those results for the period 1999-2003, but the next step is to see whether the degree of synchronization has changed over time, especially compared to countries that are not part of the euro area. One complication for comparisons of EMU members to the euro area aggregate is that these countries are part of the aggregate. To avoid this bias, correlations are calculated relative to the aggregate excluding the country in question.[57]

While the degree of monetary integration has generally increased since 1970, a number of periods can be distinguished with relatively distinct exchange rate behaviour. In the early 1970s, the Bretton-Woods system of fixed exchange rates broke down and until 1979, only relatively informal exchange rate arrangements were in place. From 1979 onwards, the Exchange Rate Mechanism (ERM) started to function, but especially in early years there were still frequent changes in parities. From about 1987 onwards, these

[55] In addition to these eleven euro area countries, Australia, Canada, Denmark, Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom and the United States are included. In the case of Australia, New Zealand and Switzerland, only quarterly industrial production data is available. Therefore, all correlations for these countries are calculated using quarterly data.

[56] Specifically, Eurostat data was used for Denmark, Italy, Norway, Sweden and Switzerland. For Japan data was used from the Cabinet Office (SNA68 series), for Spain from INE (SNA68 series) and for Canada from Statistics Canada.

[57] To facilitate this, changes in the euro area aggregate are defined as changes in the GDP-weighted average of the individual countries for both quarterly GDP and industrial production. In case of GDP, there are missing observations for a considerable number of countries in the early 1970s. For estimating the aggregate, the OECD estimate of quarterly euro area GDP is substituted for these countries.

occurred much less often, with the exception of the currency upheavals of 1992. The obvious starting point for the final period is 1999, at the introduction of the euro.

Table 3.1 Business cycle synchronization of 21 OECD countries with euro area aggregate, 1970-2003

	All countries				*Euro area countries*			
	1970:Q1-1979:Q2	1979:Q3-1987:Q3	1987:Q4-1998:Q4	1999:Q1-2003:Q4	1970:Q1-1979:Q2	1979:Q3-1987:Q3	1987:Q4-1998:Q4	1999:Q1-2003:Q4
A: Summary statistics								
GDP								
Average	0.68	0.58	0.45	0.52	0.61	0.68	0.70	0.65
Standard deviation	0.13	0.27	0.36	0.43	0.14	0.21	0.18	0.36
Minimum	0.43	-0.28	-0.20	-0.57	0.43	0.38	0.34	-0.26
Maximum	0.83	0.90	0.88	0.98	0.83	0.90	0.88	0.98
Industrial production								
Average	0.74	0.55	0.52	0.65	0.73	0.53	0.62	0.76
Standard deviation	0.20	0.29	0.30	0.35	0.24	0.33	0.24	0.29
Minimum	0.36	-0.08	-0.26	-0.11	0.36	-0.08	0.25	0.02
Maximum	0.97	0.87	0.92	0.99	0.95	0.87	0.92	0.99
B: Number of significant changes over previous period								
GDP								
Increases		1	4	3		1	3	3
Decreases		0	2	2		0	0	2
Industrial production								
Increases		0	3	9		0	2	5
Decreases		9	5	1		6	2	0

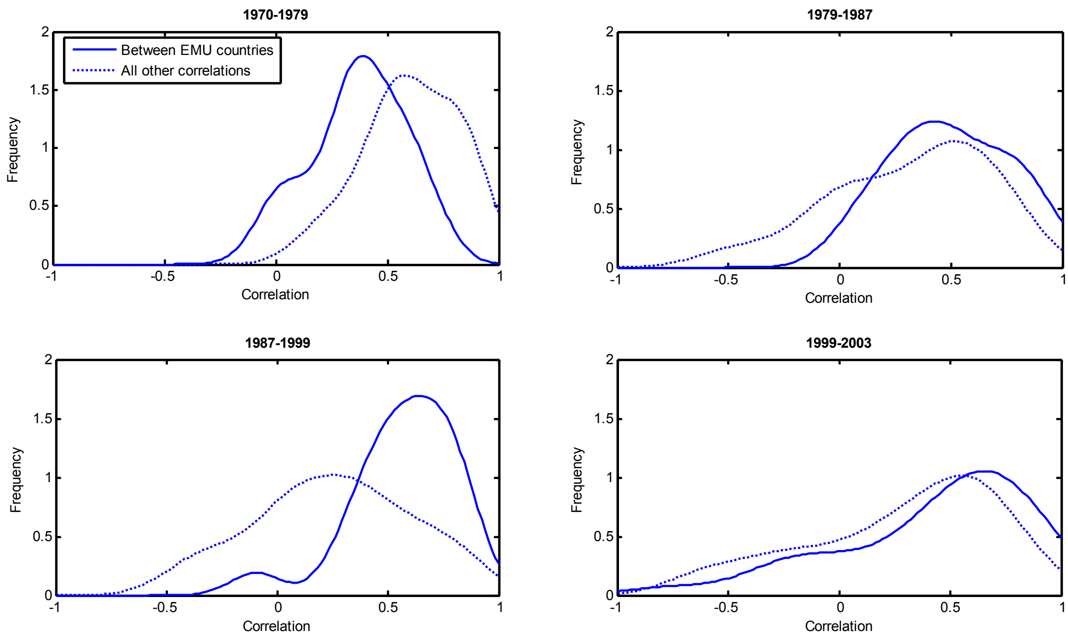
Notes: Based on correlations between detrended output in 21 OECD countries, including all euro area countries except Luxembourg, and the euro area aggregate. The non-EMU countries are Australia, Canada, Denmark, Japan, New Zealand, Norway, Sweden, Switzerland, United Kingdom and United States. In case of euro area countries, the correlation is computed excluding the country itself. In panel B, a correlation changes significantly when the 95% confidence intervals in two periods do not overlap.

Table 3.1 shows the resulting development of synchronization with the euro area over time. Panel A presents some summary statistics, both for all countries and for the subset of euro area countries. To get an indication about the importance of some the changes, Panel B shows how many countries had significantly higher or lower correlations compared with the previous period.[58] As the table makes clear, there is no clear trend in synchronization over time for either measure of output and while the correlations are generally positive, some are quite small. The correlations for the euro

[58] To be precise, a correlation coefficient changes significantly from one period to the next if the 95% confidence intervals do not overlap.

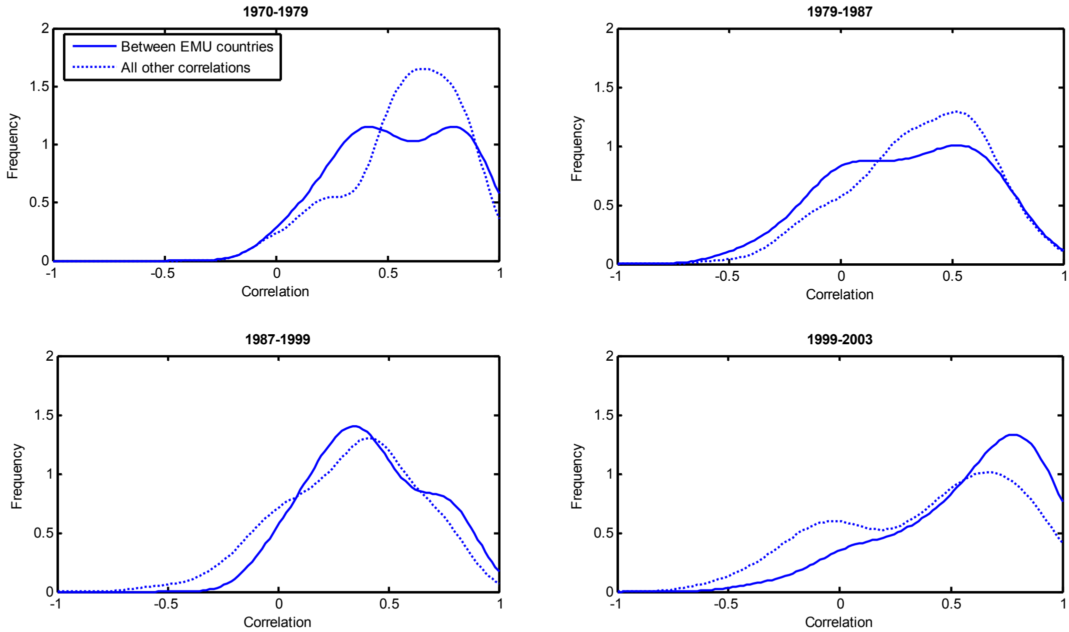
area countries are somewhat higher than the overall average, but the differences are not very large and there has only been a modest increase in the difference over time. In this respect it is remarkable that the GDP-based correlation has gone down after the start of EMU, while the correlation based on industrial production has gone up. As further evidence, the number of significant increases is not clearly larger than the number of decreases. For example, after 1999, the correlations based on industrial production increased significantly in five euro area countries, but also in four non-EMU countries. These results are akin to the conclusions by Artis (2003), who finds that there is no clear, overwhelmingly European business cycle.

Figure 3.1 Density estimates of bilateral output correlations, GDP 1970-2003



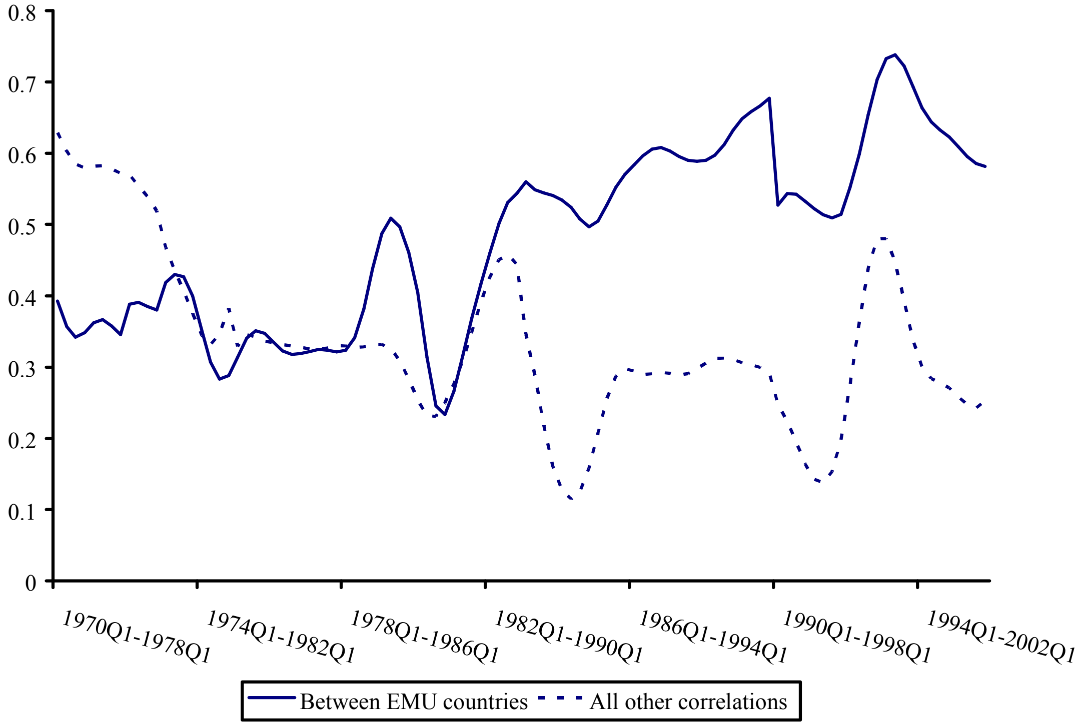
There are two obvious objections to the analysis underlying Table 3.1. First of all, although the correlations with the euro area as a whole may not show a clear pattern, a core group of euro area countries may have similar business cycles (see e.g. Forni and Reichlin, 2001). The other potential problem is that the results in Table 3.1 may not be robust to changes in the periodisation. To address the first issue, Figures 3.1 and 3.2 show kernel density estimates of bilateral correlations for the same periods as Table 3.1, while Figures 3.3 and 3.4 plot the average bilateral correlation for a moving window. The estimated densities are basically refined histograms, showing the frequency of different values of correlation coefficients.

Figure 3.2 Density estimates of bilateral output correlations, industrial production 1970-2003



If there is a core group of countries with high bilateral correlations, or if this group developed over time, a bimodal distribution for the correlations between EMU countries would show up in Figures 3.1 and 3.2. These figures show the distribution of bilateral correlations for country couples that are both EMU members, and the distribution for all other country couples (i.e. couples where at least one country is not an EMU member). However, the evidence for bimodality is by no means obvious. What does stand out in both figures is that in the period from 1970 to 1979, correlations amongst EMU countries were generally lower than all other correlations. This picture changed during the late 1980s. In the 1987-1999 period for GDP (Figure 3.1), the EMU countries were clearly more correlated amongst each other, than country couples that were not both EMU members, but for industrial production (Figure 3.2) the picture is not so clear. The pattern for GDP also did not hold clearly after 1999.

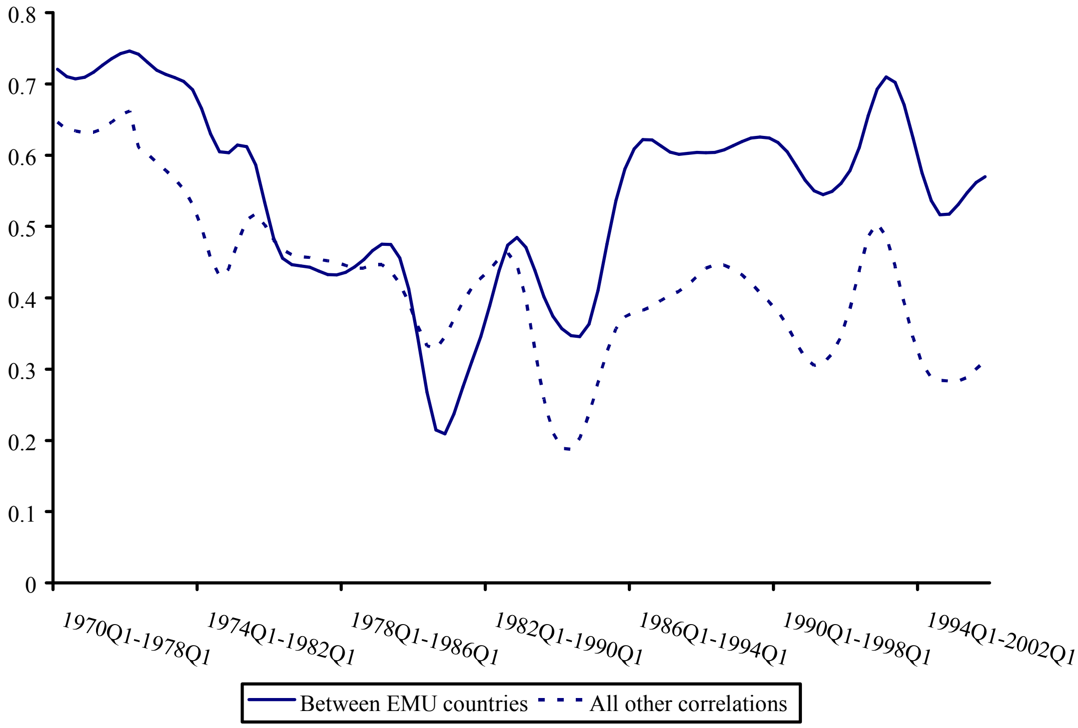
Figure 3.3 Average bilateral correlation between EMU countries and all other correlations for an 8-year moving window, GDP 1970-2003



Figures 3.3 and 3.4 provide somewhat clearer evidence. Both figures chart the average bilateral correlation for 8-year moving windows, Figure 3.3 for GDP and 3.4 for industrial production. Again, a distinction is made between correlations of EMU countries and all other correlations. The average correlation fluctuates, sometimes substantially, but since the mid-1980s, EMU correlations have on average been higher than non-EMU correlations for both output measures.[59] Still, Figures 3.1 and 3.2 showed that the distribution of correlations is quite wide and even an average correlation of 0.60 means that there has been quite some heterogeneity in the cyclical experience of euro area countries.

[59] The average correlation for EMU countries in Figure 3.3 dropped substantially around 1990. This can be traced to Portugal, which did not have a long enough time series of quarterly GDP data for earlier periods. These sample imbalances are less an issue for industrial production, as only data for Denmark and Ireland do not stretch back to 1970, but 1974 and 1975, respectively.

Figure 3.4 Average bilateral correlation between EMU countries and all other correlations for an 8-year moving window, industrial production 1970-2003



3.4 Synchronization trends in U.S. states

The past experience of euro area countries may not be representative for the future. For much of the period since 1970, monetary policy has not been coordinated and exchange rates fluctuated wildly at times. Also, the period since 1999 may simply be to short as no full business cycle has occurred since then. Indeed, the full effects of a monetary union will take even longer to materialize, as, for example, production may take a long time to concentrate geographically. To evaluate the effects of monetary union, we need to turn to an area that has already been a monetary union for many decades.

The United States is a good candidate as it is similar in size to the euro area and it is also a developed country. Ever since 1935, all monetary policy decisions have been in the hands of the Federal Reserve and before that, a common currency was in use and individual states could not hamper inter-state commerce. Technological progress over the past century has reduced the cost of transport and communications, which may have made regional specialization more attractive over time.[60]

To analyze long-run trends in business cycle synchronization, state personal income is the only available measure. Gross state product (the state analogue of GDP) is only available from 1977 onwards on a consistent basis, while employment data go back to 1969. In contrast, the personal income data from the U.S. Bureau of Economic Analysis (BEA) are available from 1929 onwards.[61] No price data is available at the state level, so instead the implicit GDP deflator is used.

Table 3.2 Business cycle synchronization of personal income in U.S. states with U.S. aggregate personal income, 1929-2004

	1929-1947	1948-1966	1967-1985	1986-2004	1929-1966	1967-2004
Summary statistics						
Average	0.88	0.67	0.76	0.68	0.85	0.72
Standard deviation	0.08	0.22	0.19	0.22	0.09	0.18
Minimum	0.61	0.11	0.17	0.07	0.54	0.25
Maximum	0.97	0.93	0.96	0.94	0.96	0.92
Number of significant changes over previous period						
Increases		0	3	0		0
Decreases		5	0	0		7

Notes: Based on correlations of annual state personal income for U.S. states excluding Alaska and Hawaii, including the District of Columbia. Personal income is deflated using the U.S. GDP deflator and detrended with the Baxter-King band pass filter (fluctuations between 1 and 8 years). Each state's cycle is correlated to the U.S. aggregate, excluding the state in question. A correlation changes significantly when the 95% confidence interval of the coefficients in one period does not overlap the interval in the next period.

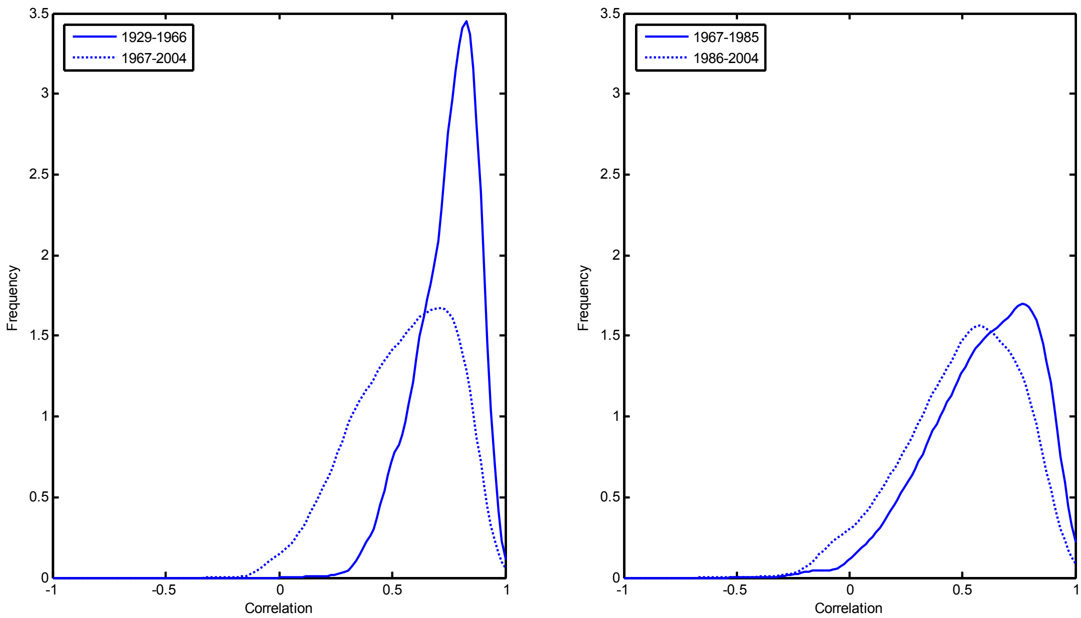
Table 3.2 shows the results for a number of different periods. As there have been no major shifts in the degree of monetary integration, the period is first divided into four periods of equal length and next divided into two periods. As the table makes clear, the average correlation was highest in the first period, 1929-1947, which included both the Great Depression and the wartime economic boom. The minimum correlation of 0.61 in this period is another indication that this was a period of relatively homogenous

[60] See also Sleijpen (2001) for more on the United States as a monetary and fiscal union.
[61] The personal income measure in the U.S. national accounts includes household income from all sources, including government transfers as well as income of non-profit institutions. As such, it covers around 80 percent of GDP.

economic performance across states. The post-war periods shows much greater divergence with a lower average correlation and a greater spread. The bottom panel of the table shows that there have been relatively few significant changes in correlation: of the 49 states covered,[62] only seven or eight showed a significant change. Compared to the results in Table 3.1, the cycles of U.S. states after 1948 are not much more similar than the business cycles of countries in the euro area.

Again, similar criticisms can be raised about the possible cluster formation (for example in certain regions) and the arbitrary periodisation. Figure 3.5 shows density estimates of the correlations for each couple of states. The chart on the left-hand side compares the period up to 1966 to the period afterwards, and the right-hand side divides the 1967-2004 period in two. These charts show a comparable pattern to that seen in Table 3.2 with a very high degree of synchronization in early periods and lower synchronization from around 1970 onwards. Compared to Figures 3.1 and 3.2 though, the spread of bilateral correlations is smaller in case of the U.S. states.

Figure 3.5 Density estimates of the bilateral personal income correlations, 1929-2004



[62] Alaska and Hawaii are excluded because they have not been part of the Union since 1929. The District of Columbia is included.

Figure 3.6 addresses the issue of periodisation. All bilateral correlations are calculated for each 8-year period between 1929 and 2004 and the average is plotted. The figure shows considerable variation with average correlations fluctuating between 0.2 and 0.8. The pattern is also broadly comparable to that shown in Table 3.2. The figure suggests economy-wide developments, such as the Great Depression and the following wartime boom, or the oil crises and economic stagflation in the 1970s and early 1980s have similar effects across most states. However, there are also periods where divergence is much greater.

Figure 3.6 Average bilateral correlation between U.S. states for an 8-year moving window, personal income 1929-2004

In summary, the U.S. experience suggests that a monetary union is no guarantee for perfectly synchronized business cycles and economic integration does not inexorably lead to more similar business cycles. Even though the average correlation seems to be somewhat higher amongst U.S. states than between euro area countries, the differences are not large. The development over time suggests that there are periods where U.S.-wide developments dominate, such as the Great Depression, but also that there are periods of greater divergence across states. This is in line with the results of Partridge and Rickman

(2005), who find that co-movement between states has decreased since the late 1960s due to a less volatile aggregate economy.[63]

3.5 The determinants of synchronization

Since the seminal paper of Frankel and Rose (1998), the search for determinants of business cycle synchronization has taken a great flight. However, these studies cannot agree on more than the original finding by Frankel and Rose (1998) that more intensive trade links between two countries stimulates synchronization.[64] The analysis in this section builds on this literature and first focuses on finding a set of robust explanatory variables. This analysis is comparable to the Extreme Bounds Analysis of Baxter and Kouparitsas (2004), but covers 21 OECD countries and considers a more extensive list of potential explanatory variables. Furthermore, instead of the very restrictive criterion for robustness of Leamer (1983), the criterion of Sala-i-Martin (1997) is followed.[65]

Once a set of robust explanatory variables is identified, the remainder of the section focuses on estimating a model for synchronization that incorporates these variables and analyzing the implications for EMU. This analysis makes a number of contributions to the literature. First of all, as the density estimates of Figures 3.1 and 3.2 already showed, correlation coefficients are skewed and hence, not normally distributed. For valid inference in the regressions, the correlation coefficients are transformed, so that they are no longer bounded between -1 and 1.

Second, the issue of endogeneity of trade is dealt with in a more substantive way than in previous studies. The basic problem here is that countries with intense trade relations are more likely to link their currencies, either explicitly or implicitly. This implies that these countries will have similar monetary policies – and possibly other policies – that may synchronize their business cycles. So it is not only trade that causes the business cycles to be correlated but also the similarity of economic policies. Neglecting these other variables in the regression specification renders the trade

[63] The correlation of output between two states will *ceteris paribus* be lower if shocks that are common to both states, such as U.S.-wide shocks are less common. See e.g. McConnell and Perez-Quiros (2000) or Stock and Watson (2003) for more on the decreased volatility of the U.S. economy.

[64] For a survey of research into the determinants of synchronization, see de Haan, Inklaar and Jong-A-Pin (2005).

[65] See Appendix 3.A for more details.

coefficient biased and inconsistent. Frankel and Rose (1998) and most subsequent studies therefore employ instrumental variables estimation, using gravity variables as instruments. However, this is not an adequate solution, since the gravity variables are likely to affect other variables that influence business cycle synchronization as well, like participation in a currency union. This problem is avoided by estimating a multivariate model, including policy variables as well as structural characteristics.

The third topic is the effect of specialization on business cycle synchronization. If the degree of specialization between two countries is high, most trade will be inter-industry, and industry-specific shocks will lead to diverging business cycles. However, a dominant role for intra-industry trade can explain the positive association between trade and synchronization that has been found in the literature. Despite these theoretical arguments, this issue has received only scant empirical attention. Gruben *et al.* (2002) include inter-industry and intra-industry trade in their business cycle synchronization model and claim that the effects of both variables are different. However, this conclusion is based on unreliable estimates as the correlation between inter- and intra-industry trade is very high. Imbs (2004) accounts for the effect of inter-industry trade by including a measure of industrial specialization. The approach taken here is similar, but in addition to industrial structure, the structure of overall exports and the share of (bilateral) intra-industry trade are used to test the theoretical foundations of the trade relationship more directly.

The final issue is to what extent the relationship between trade intensity and business cycle synchronization is robust across different country pairs. Is the effect of trade on business cycle synchronization the same for country pairs that are already highly synchronized, like Germany and the Netherlands, and countries which are not, like for example Germany and Japan? Or is the effect of trade on business cycle correlations driven by (outlying) country pairs such as the US and Canada? To examine the importance of sample heterogeneity and outliers, the methods of quantile regressions and least-trimmed squares are employed, respectively.

The main findings are the following. Trade intensity is found to affect business cycle synchronization, but the effect is much smaller than reported by Frankel and Rose (1998) and Hausman (1978) tests show that in the multivariate models, estimation using ordinary least squares is no longer inconsistent. Furthermore, apart from the level of trade, specialization has a strong impact on business cycle synchronization. In addition, similar monetary and similar fiscal policies have a positive impact on business cycle synchronization. The impact of these factors on business cycle synchronization is about as large as the impact of trade intensity. Finally, the results suggest that the effect of trade on business cycle synchronization does not suffer from sample heterogeneity and is robust for outlying observations.[66]

The remainder of the section is organized as follows. First, the methodology and the data sources and methods are described. Thereafter, the estimation results are presented and the economic relevance of the findings is discussed. The final part shows the results of the quantile and least trimmed squares regressions.

Methodology

Theoretically, trade intensity has an ambiguous effect on the co-movement of output. Standard trade theory predicts that openness to trade will lead to increased specialization in production and inter-industry patterns of international trade. If business cycles are dominated by industry-specific shocks, trade-induced specialization leads to decreasing business cycle correlations.[67] However, if trade is dominated by intra-industry trade industry-specific shocks may lead to more symmetric business cycles. Furthermore, in case of intensive trade relations economy-wide shocks in one country will generally have an effect on demand for goods from the other country.

The question how to disentangle the effect of intra-industry and inter-industry trade has been dealt with in different ways in the literature. Imbs (2004) includes an industrial specialization measure to capture the impact of inter-industry trade. Gruben *et al.* (2002)

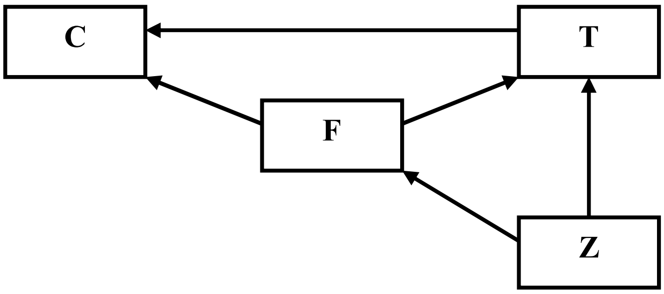
[66] The paper that comes closest to the analysis here is Imbs (2004), who also finds that the effect of trade on business cycle synchronization is less than that reported by Frankel and Rose (1998). There are, however, a number of important differences between both studies. The methodology is quite different as the primary interest is in the effect of trade intensity on output correlation. Furthermore, a much longer list of potential determinants of business cycle synchronization is analyzed here. Imbs (2004), for instance, does not take the role of monetary and fiscal policy into account, which is found to be important. Imbs also does not examine how sensitive his findings are for sample heterogeneity and outliers.

[67] However, as pointed out by Frankel (2004), a positive shock at one point in the chain of value added in a country will tend to have positive spillover effects at the other points along the chain in other countries. Thus trade in intermediate products gives rise to positive correlations but may be recorded as inter-industry trade.

take a more direct approach and split up trade in inter- and intra-industry trade. In a regression in which both intra-industry and inter-industry trade are included, they find that intra-industry trade has a positive effect and that the effect of inter-industry is insignificant. An important problem with this approach is that intra-industry trade is highly correlated with inter-industry trade; in the dataset used here, this correlation is 0.82. This means that including both variables simultaneously leads to serious multicollinearity problems. Therefore the approach of Imbs (2004) is followed and his solution is taken one step further. Instead of relying only on specialization measures based on industrial structure, measures based on the structure of exports, and the share of intra-industry trade are also used. These measures will be discussed in more detail below.

Frankel and Rose (1998) acknowledge the possible contrasting effects of inter- and intra-industry trade on business cycle synchronization, but focus on the net effect of total trade on output co-movement. However, even identifying the net effect of trade is not straightforward since trade intensity is endogenous, which makes an OLS regression of business cycle synchronization on trade intensity inappropriate. Frankel and Rose (1998) deal with this problem by using gravity variables (distance, border dummy, common language dummy) as instruments to identify the effect of trade on business cycle correlation. However, as pointed out by Gruben *et al.* (2002), this is not appropriate if the gravity variables (Z) not only affect bilateral trade intensity (T) but are also possibly related to some other variables (F) that affect business cycle synchronization (C), as illustrated in Figure 3.7. For instance, neighbouring countries are more likely to coordinate their monetary policies, or even to have a common currency, than countries that are further away from each other. In turn, the introduction of a single currency will contribute to reducing trading costs both directly and indirectly, e.g., by removing exchange rate risks (and the cost of hedging) and diminishing information costs (De Grauwe and Mongelli, 2005).

Figure 3.7 The Relationship between business cycle correlation (*C*), trade (*T*), gravity variables (*Z*) and other variables (*F*)



The regression model that corresponds to the figure above is:

$$
\begin{aligned}
&C = \beta_1 T + \beta_2 F + \varepsilon \\
&T = c_1 Z + c_2 F + \nu \quad . \\
&F = c_3 Z + \omega
\end{aligned}
\tag{3.4}
$$

The model shows that the business cycle correlation depends on bilateral trade as well as other policy-related and structural variables. Some of these variables may be influenced by the exogenous gravity variables, while in turn affecting trade intensity. Broadly speaking, these variables can be grouped into the following categories: (1) specialization (see, e.g., Imbs, 2004); (2) monetary integration (see, e.g., Rose and Engel, 2002); (3) financial integration (see, e.g., Imbs, 2004); and (4) similarity of fiscal policies (see, e.g., Clark and van Wincoop, 2001). Apart from these variables many others have been suggested that may be related to business cycle synchronization (see chapter 6 in De Haan, Eijffinger and Waller (2005) for an extensive discussion).

To identify the other variables to be included in the model, an Extreme Bounds Analysis is used to examine which variables are robustly related to business cycle synchronization in the OECD area, following Baxter and Kouparitsas (2004). Using a much longer list of potential explanatory variables than examined by Baxter and Kouparitsas a number of robust variables are identified, including the similarity of monetary policy (proxied by the correlation of short-term interest rates) and the similarity of fiscal policy (proxied by the correlation of cyclically-adjusted budget deficits). In contrast to Baxter and Kouparitsas (2004) the robustness criteria of Sala-i-Martin (1997) are used since Leamer's (1983) EBA is extremely restrictive. Appendix Table 3.1 shows the variables that have been used in the analysis and whether they are robust explanatory variables of the business cycle correlation between two OECD countries. When testing for the robustness of these variables, care was taken not to include other proxies for the same "driving force" in the set of control variables. This is especially relevant for financial integration and specialization, since three measures of financial integration and specialization are under consideration (see below for more details on these measures).

Once a suitable set of explanatory variables has been identified, the appropriate method to estimate the model above depends on the correlation between the error terms of the three equations. Given the exogeneity of gravity variables, it is crucial whether ν and ε are correlated. If so, using OLS for the first equation results in inconsistent estimates and instrumental variables estimation should be preferred. If not, OLS estimates are consistent and at least as efficient. A Hausman (1978) test is used to test whether IV estimates are significantly different from OLS estimates. If there is no significant difference between these estimates, we can conclude that OLS gives consistent results.

Data sources and methods

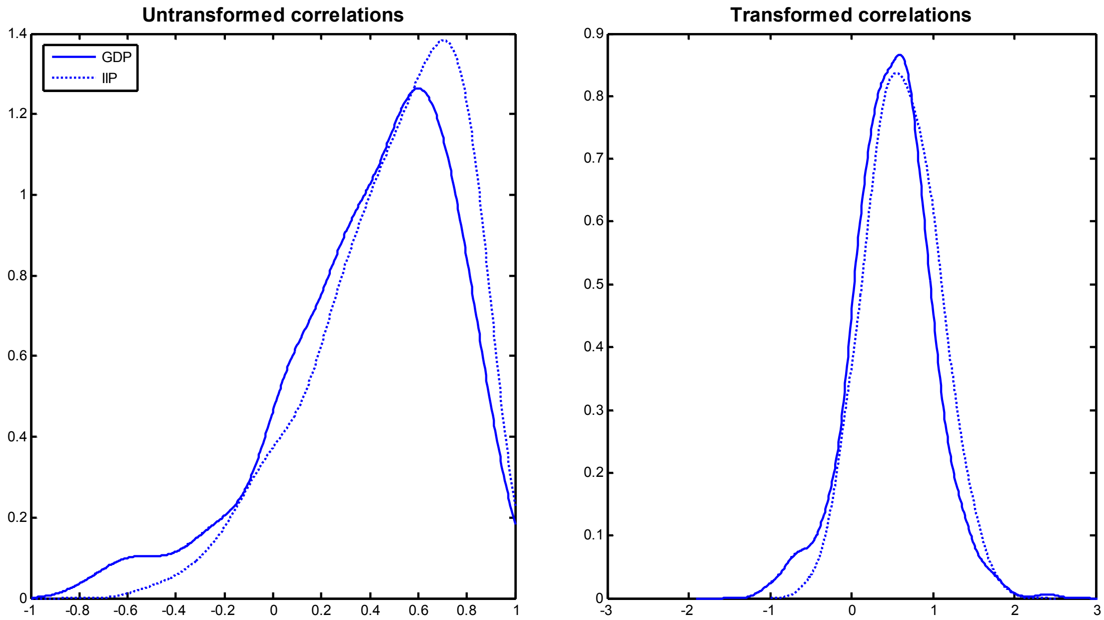
As in Section 3.3 on synchronization trends in the OECD, both GDP and industrial production are used as measures of economic activity and both variables are detrended using the Baxter-King band pass filter. As Figures 3.3 and 3.4 showed, synchronization tends to fluctuate over time and there is no obvious way to split the sample period in relatively homogenous sub-periods. For the regression analysis, the sample is therefore split into three periods of equal length (i.e. 11 years: 1970-1981, 1981-1992 and 1992-2003), resulting in a maximum of 630 observations (0.5*(3*21*20)).[68] For the quantile regression results shown below, the sample is split in eight periods of equal length in order to increase the number of observations.[69]

As Figures 3.1 and 3.2 showed, the set of correlations is generally not normally distributed. Up to here, this was not problematic, but the residuals in the regression need to be normally distributed for valid inference. To resolve this, Fisher's *z*-transformation of the correlation coefficients is used as the dependent variable. The transformed correlation coefficients are calculated as $C^t = 1/2\ln((1+C)/(1-C))$, where C is the pair-

[68] Frankel and Rose (1998) followed a similar approach, using four periods of about 9 years.
[69] The results are generally robust to distinguishing from two up to eight different periods.

wise correlation coefficient for each country couple. After transformation, the correlation coefficient is no longer bounded at -1 and 1, but unbounded instead. As a result the transformed correlations will be normally distributed (see David, 1949). This issue has not been addressed in most previous papers using these types of model, presumably under the assumption that the deviation from normality is sufficiently small. Figure 3.8 shows density estimates of all untransformed correlations (left-hand side) and the transformed correlations. While the untransformed correlations are clearly skewed, the *z*-transformation mostly removes this.

Figure 3.8 Estimated density plots of untransformed and transformed business cycle correlations



In previous studies on the determinants of business cycle synchronization various indicators of trade intensity have been used.[70] For instance, Frankel and Rose (1998) employ total trade (i.e. exports X and imports M) between two countries (i,j) scaled by total GDP (Y) or total trade.[71] Instead of using the sum of trade or GDP of the two

[70] The source for all the trade data in this study is the new database by Feenstra *et al.* (2005).
[71] As pointed out by Otto *et al.* (2001), the first measure suffers from obscuring one-way interdependence, the second suffers from not measuring the relative importance of trade in the total economy. Note that when using GDP as a scaling factor, GDP at current national prices is converted to U.S. dollars using

countries as scaling factor, some authors prefer scaling by the product of GDP or trade of the two countries concerned (see, for instance, Clark and van Wincoop, 2001) as this indicator is not size-dependent. An alternative indicator is suggested by Otto *et al.* (2001), who take the maximum of:

$$\sum_t \frac{X_{ijt} + M_{ijt}}{Y_{it}}, \sum_t \frac{X_{ijt} + M_{ijt}}{Y_{jt}} \quad (3.5)$$

They argue that what matters is whether or not at least one country is exposed to the other. In this measure, total trade can also be used for normalization. As a result, six different trade intensity measures have been calculated. Table 1 shows the correlation matrix of these indicators. As these measures are (imperfect) proxies for trade intensity and it is not obvious which one is to be preferred, they are combined into a single measure using principal component analysis. The preferred trade intensity measure is therefore based on the common variation in the six individual trade intensity measures. This combined measure is based on the largest eigenvalue, which accounts for 64 percent of the total variance.[72]

Table 3.3 Correlation coefficients between trade intensity measures

	TINT2	TINT3	TINT4	TINT5	TINT6
TINT1	0.52*	0.84*	0.73*	0.27*	0.58*
TINT2		0.58*	0.52*	0.60*	0.48*
TINT3			0.57*	0.29*	0.78*
TINT4				0.64*	0.57*
TINT5					0.51*

Notes: * denotes correlation significantly different from zero at 5% level.
TINT1: bilateral trade, normalised by total trade of the two countries.
TINT2: normalised by minimum of total trade of the two countries,
TINT3: normalised by the product of total trade of the two countries.
TINT4-6: same, but with GDP.

As discussed in the previous section, three indicators of *specialization* are distinguished, namely measures based on industrial specialization, export similarity and the share of intra-industry trade. Imbs (2004) suggests the following measure for industrial specialization:

purchasing power parities from the OECD (2002a) to take price differences between countries into account. All trade data are already converted using current exchange rates.

[72] The first eigenvalue is four times larger than the second. Furthermore, a measure based on the largest two eigenvalues has a correlation of 0.99 with the measure based on only the largest eigenvalue.

(3.6) $$\frac{1}{T}\sum_{t}\sum_{n=1}^{N}|\, s_{tni} - s_{tnj} \,|,$$

where s_{tni} denotes the GDP share of industry n at time t in country i. Apart from the index suggested by Imbs, the squared difference instead of the absolute difference of output shares can be used. Following Baxter and Kouparitsas (2004), these specialization measures are recast as similarity measures by subtracting the specialization measure from one. In addition, the correlation of output shares is used. These three industrial similarity indicators are constructed using the 60-industry database of the Groningen Growth and Development Centre (GGDC, 2005b), which has data on 56 industries covering the entire economy at the 2-digit and sometimes 3-digit level of industry detail (according to the ISIC revision 3 classification).[73] As might be expected, the three measures of output similarity are highly correlated (between 0.87 and 0.96), so following similar reasoning and criteria as for the trade intensity measures, the first principal component is used in the regressions as the first indicator of specialization.[74]

Furthermore, following Baxter and Kouparitsas (2004), the similarity of exports is used as the second main indicator of specialization. As these authors point out, countries with similar baskets of traded goods will be affected similarly in the event of sector-specific shocks hitting their export and/or import sectors. Using the trade data by commodity (at the 4-digit SITC level of detail) of Feenstra *et al.* (2005), export shares are calculated for each country. The same three similarity measures as for output shares are calculated for export shares. The correlation between these export similarity measures varies between 0.54 and 0.84, and the first principal component accounts for 78% of the variance. Therefore, this measure is used as the second specialization indicator.

The final indicator of specialization is the share of bilateral trade that can be attributed to intra-industry trade, *IIT*. This index is defined as:

[73] See www.ggdc.net for a more thorough documentation of this database, as well as the most recent version.
[74] The first principal component accounts for 94 % of the variance.

$$(3.7) \qquad IIT_{ij} = 1 - \frac{\left|\sum_k \left(E_{ij}^k - E_{ji}^k\right)\right|}{\sum_k \left(E_{ij}^k + E_{ji}^k\right)}.$$

The share of intra-industry trade is calculated as one minus the absolute difference between exports of industry *k* from country *i* to country *j* and exports from country *j* to country *i*, divided by total bilateral trade (see Grubel and Loyd, 1971). The trade data by commodity of Feenstra *et al.* (2005) are allocated to industries using a detailed concordance.[75]

Financial linkages could result in a higher degree of business cycle synchronization by generating large demand side effects. For instance, a decline in a particular stock market could induce a simultaneous decline in demand in other countries if investors in these countries have invested in this particular stock market. Furthermore, contagion effects that are transmitted through financial linkages could also result in heightened cross-country spillover effects of macroeconomic fluctuations. However, international financial linkages could also stimulate specialization of production through the reallocation of capital in a manner consistent with countries' comparative advantages. Three indicators of *financial integration* are considered: the correlation of changes in stock market indexes, a dummy for capital account restrictions, and the (absolute) difference between the net foreign asset (NFA) positions of a country couple.[76]

The stock market data are from the IMF's *International Financial Statistics* and the measure that is used is the correlation of annual growth rates. The capital account variable is based on information provided by Lane and Milesi-Ferretti (2001) and updated using the IMF publication *Exchange arrangements and exchange restrictions*, which gives an overview of capital and current account restrictions for each country. The indicator equals one if at least one of the two countries had capital account restrictions during the period considered. The source of the NFA data is again Lane and Milesi-Ferretti (2001). They present two estimates, one based on cumulated current account data and one based on cumulated capital accounts. As the capital account-based measure is

[75] Industries are defined at the 4-digit level of the international standard classification (ISIC rev. 2). See http://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html.
[76] The latter two measures are also employed by Imbs (2004).

available for fewer years in most countries and (in theory) they should measure the same phenomenon, the cumulated current accounts are used.

Estimation results

The first two rows of Panel A of Table 3.4 shows a replication of the main results of Frankel and Rose (1998), i.e. the OLS and instrumental variables (IV) estimates of the effect of trade on business cycle correlations using the same trade measures as in their study. In addition to the instruments used by Frankel and Rose (1998), i.e. distance, an adjacency dummy, and a dummy for common language, a variable measuring geographical remoteness and a dummy for common legal origin are also included.[77]

The OLS and IV estimates of the trade coefficient are positive and highly significant and comparable for the two measures of economic activity. Like Frankel and Rose, the coefficients are smaller and less significant when bilateral trade intensity is normalized by output. The IV estimates are similar in magnitude as those reported by Frankel and Rose (1998) and considerably higher than the OLS estimates. Indeed, Hausman (1978) tests show that the IV estimates are significantly different from the OLS estimates, suggesting that the OLS estimates are biased.

[77] All these instruments are highly significant in explaining trade intensity and the F-statistic from the test of the joint significance of all variables in the first-stage regression with gravity variables explaining trade is 157. Legal origin has also been used to directly explain output co-movement (e.g. Otto *et al.*, 2001) but it can be argued that the main effect of a common legal origin is via trade: the correlation between legal origin and trade intensity is 0.40, while the correlation with the GDP and IP correlations are 0.23 and 0.11, respectively. As the 95% lower bound of the legal origin-trade intensity correlation is 0.27, the link with trade is significantly stronger than the link with output correlations. From a conceptual point of view, it also seems reasonable that a common legal system will facilitate trade links, while the direct link with synchronization is more elusive.

Table 3.4 The effect of trade on business cycle synchronization, replication of the Frankel-Rose model with the current dataset

	OLS		IV	
	IIP	GDP	IIP	GDP
Panel A, Estimation results				
(1) Bilateral trade, normalised by total trade	0.031*	0.025*	0.060*	0.061*
	(0.005)	(0.006)	(0.008)	(0.011)
(2) Bilateral trade, normalised by total GDP	0.009*	0.010*	0.016*	0.016*
	(0.001)	(0.002)	(0.002)	(0.003)
(3) Bilateral trade, factor score	0.074*	0.086*	0.125*	0.140*
	(0.010)	(0.014)	(0.015)	(0.021)
(4) Bilateral trade, factor score, transformed correlation	0.127*	0.125*	0.204*	0.203*
	(0.018)	(0.021)	(0.024)	(0.030)
Hausman test (H0: OLS is consistent)				
Bilateral trade, normalised by total trade			21.0*	18.3*
Bilateral trade, normalised by total GDP			24.6*	11.4*
Bilateral trade, factor score			22.2*	13.3*
Bilateral trade, factor score, transformed correlation			24.5*	14.5*
Panel B, Standardized coefficients				
Bilateral trade, normalised by total trade	0.081	0.072	0.070	0.077
Bilateral trade, normalised by total GDP	0.080	0.089	0.079	0.081
Bilateral trade, factor score	0.074	0.084	0.100	0.106
Bilateral trade, factor score, transformed correlation	0.126	0.123	0.160	0.151
95% confidence interval of standardized coefficient [Lower bound – Upper bound]				
Bilateral trade, normalised by total trade	[0.06 - 0.11]	[0.04 - 0.10]	[0.05 - 0.09]	[0.05 - 0.11]
Bilateral trade, normalised by total GDP	[0.06 - 0.10]	[0.06 - 0.12]	[0.06 - 0.10]	[0.06 - 0.11]
Bilateral trade, factor score	[0.05 - 0.09]	[0.06 - 0.11]	[0.08 - 0.12]	[0.08 - 0.14]
Bilateral trade, factor score, transformed correlation	[0.09 - 0.16]	[0.08 - 0.16]	[0.12 - 0.20]	[0.11 - 0.19]

Note: * denotes significantly different from zero at 5% level (coefficients) or null hypothesis rejected at 5% level. Dependent variable are the bilateral output correlations. Heteroscedasticity-consistent standard errors are in parentheses. The standardized coefficients are calculated by dividing the coefficient by the standard deviation of the underlying data series. The number of observations is 630 for the IIP regressions and 472 for the GDP regressions.

Row (3) of panel A of Table 3.4 shows the results using the preferred indicator of trade intensity (the first principal component of six different measures of trade), while row (4) presents the results after transforming the output correlations. The coefficients of the preferred trade indicator are highly significant, which suggests that the qualitative conclusion that trade intensity is positively related to business cycle correlation is not sensitive to the measurement of trade intensity. Transforming the dependent variable yields higher coefficients, but due to the transformation it is not straightforward to compare the coefficients with the estimates of rows (1)-(3). In order to make a meaningful comparison, Panel B of the table presents the standardized coefficients, calculated by dividing the coefficients in Panel A by the standard deviations of the respective trade series. This gives the effect on the business cycle correlation from a change in trade intensity of one standard deviation, evaluated at the mean. The effect for the model with transformed correlation coefficients is calculated by running the reverse *z*-transformation on the estimated effect. Below the point estimates, the 95% upper and lower bound are shown. These results suggest that the use of the transformed dependent variable leads to a somewhat stronger impact of trade on business cycle synchronization.

Table 3.5 shows the estimation results for the model outlined in Figure 3.7. For the variables to be included in *F*, the results of the Extreme Bounds Analysis (EBA) as described in Appendix 3.A are used. A separate analysis is run for each combination of financial integration and specialization measures. For the financial integration measures only the correlation of stock returns turns out to be a robust explanatory variable for synchronization while the capital account restrictions and NFA measures fail to pass the test. Therefore only regressions with the stock market indicator are shown. In contrast, all three specialization measures appear robustly related to business cycle synchronization and are therefore each included in a separate regression model.[78]

It follows from Appendix Table 3.1 that apart from the correlation of stock market returns and the specialization measures, other variables are also considered robust in the sense that in regressions with different control variables, the sign and significance of the coefficients remains stable.[79] The correlation of short-term interest rates and the correlation of cyclically-adjusted budget deficits are robustly related to business cycle synchronization for both GDP and industrial production correlations. For the GDP-based measure of synchronization, exchange rate variability is also robust.[80] It follows from Table 3.5 that almost all explanatory variables are significant with the expected sign. So a higher correlation between monetary policy or fiscal policy, more similar industrial and export structures, a higher share of intra-industry trade, and less exchange rate variability are related to more similar business cycles.

[78] The measure of industrial similarity is not robust with GDP as the dependent variable, but it is included to facilitate the comparability of results across specifications.
[79] See the Appendix for a more precise definition.
[80] For the industrial production correlations, measures reflecting differences in capital stocks and arable land are also robust for some combinations of financial integration and specialization measures. Since they frequently fail this test and are also not robustly related to the GDP-based measure of synchronization, they are not included here.

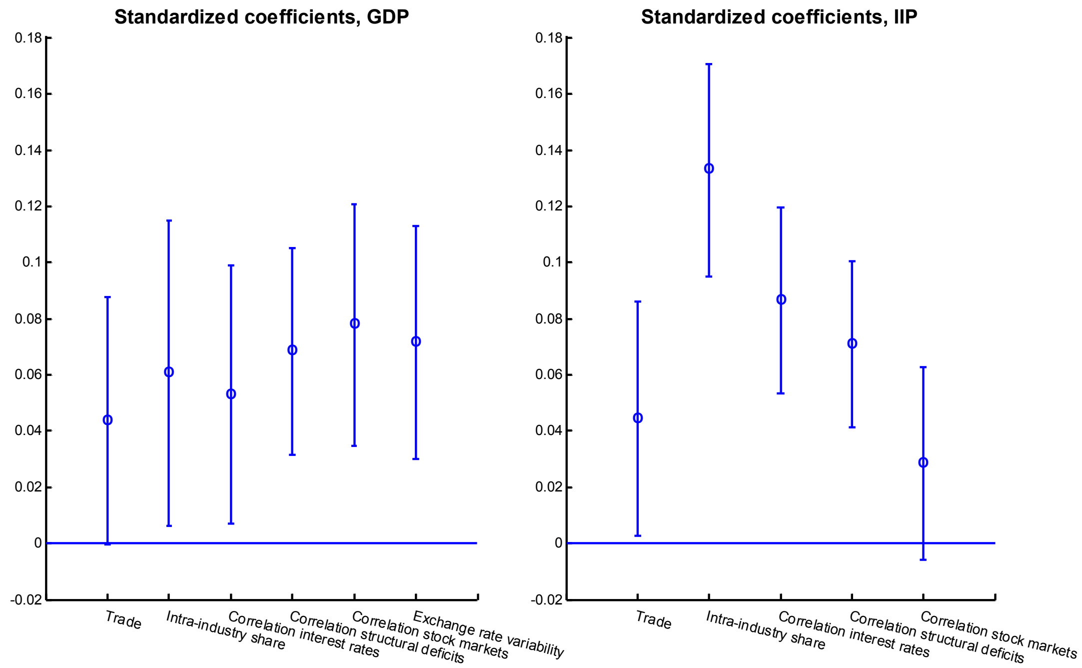
Table 3.5 Effect of trade on business cycle synchronization in a multivariate model

Specialisation measure:	*Industrial similarity*		*Export similarity*		*Share of intra-industry trade*	
GDP	OLS	IV	OLS	IV	OLS	IV
Trade	0.043*	0.054*	0.053*	0.121*	0.044	0.115*
	(0.020)	(0.026)	(0.021)	(0.036)	(0.023)	(0.040)
Specialisation measure	0.032	0.031	0.064*	0.050*	0.346*	0.177
	(0.024)	(0.024)	(0.021)	(0.021)	(0.159)	(0.175)
Correlation of short-term interest rates	0.239*	0.236*	0.124*	0.112	0.129*	0.130*
	(0.055)	(0.057)	(0.057)	(0.059)	(0.057)	(0.058)
Correlation of cyclically-adjusted budget deficits	0.172*	0.171*	0.143*	0.137*	0.136*	0.133*
	(0.036)	(0.036)	(0.038)	(0.038)	(0.037)	(0.038)
Correlation of stock markets	0.308*	0.303*	0.214*	0.202*	0.225*	0.216*
	(0.080)	(0.080)	(0.065)	(0.064)	(0.064)	(0.063)
Exchange rate variability	-1.600*	-1.513*	-1.552*	-1.089*	-1.548*	-1.165*
	(0.483)	(0.497)	(0.46)	(0.487)	(0.458)	(0.478)
Number of observations	335	335	459	459	459	459
Industrial production						
Trade	0.080*	0.088*	0.069*	0.113*	0.043*	0.080*
	(0.021)	(0.026)	(0.019)	(0.023)	(0.021)	(0.026)
Specialisation measure	0.070*	0.069*	0.118*	0.105*	0.761*	0.657*
	(0.018)	(0.018)	(0.016)	(0.016)	(0.111)	(0.117)
Correlation of short-term interest rates	0.374*	0.372*	0.221*	0.217*	0.211*	0.214*
	(0.042)	(0.042)	(0.042)	(0.043)	(0.041)	(0.041)
Correlation of cyclically-adjusted budget deficits	0.125*	0.126*	0.157*	0.155*	0.143*	0.143*
	(0.034)	(0.034)	(0.030)	(0.030)	(0.030)	(0.030)
Correlation of stock markets	0.161*	0.156*	0.064	0.057	0.082	0.077
	(0.060)	(0.059)	(0.052)	(0.052)	(0.050)	(0.050)
Number of observations	378	378	556	556	556	556
Hausman test (H0: OLS is consistent, critical 5% value: 12.6)						
GDP		0.32		6.83		5.00
Industrial production		0.28		8.51		3.90

Notes: The dependent variable is the transformed output correlation. * denotes coefficient significantly different from zero at 5% level. Heteroscedasticity-consistent standard errors are in parentheses. IV includes gravity instruments (distance, geographical remoteness and dummies for a common border, language and legal origin) and all explanatory variables except trade.

The main finding in Table 3.5 is that the trade coefficients are much smaller than those previously found: the coefficient of trade intensity with GDP correlation as dependent variable is only half as large as in Table 3.4 for both the OLS and IV specification. In addition to the gravity variables that were used as instruments in Table 3.4, the other explanatory variables are included as instruments too (except trade); this specification corresponds to the second line of equation (3.4). The Hausman tests show that OLS and IV estimates are not significantly different so the consistency of OLS can no longer be rejected. Because Frankel and Rose (1998) did not specify a full model, they overestimated the impact of trade on output correlation.

Figure 3.9 Standardized coefficients of explanatory variables with 95% confidence intervals



Note: The standardized coefficients are based on the OLS regressions, using intra-industry trade as the measure of specialization.

Figure 3.9 shows the standardized coefficients of all the variables included in the model with intra-industry trade as the specialization measure. The point estimate, as well as the 95% upper and lower bounds are shown. It follows that the point estimates of almost all standardized coefficients – like the correlation of short-term interest rates or of cyclically-corrected budget deficits – is larger than the impact of trade intensity. The upper and lower bounds show that these differences are mostly not significant. Still, the evidence suggests that variables that reflect common economic policies and specialization are at least as important as strong trade ties for synchronization.

Finally, Figure 3.10 compares the standardized coefficients of the three specialization measures that are used. Again, the point estimate as well as the 95% upper and lower bounds are shown. In this figure, industrial similarity has the lowest impact. In view of the upper and lower bounds of the coefficients one has to be careful in drawing too strong conclusions, but the evidence suggests that trade-based specialization measures have a larger impact on business cycle synchronization than industry-structure-based specialization measures. This is most visible for the coefficients of the models based on industrial production.

Figure 3.10 Standardized coefficients of specialization measures with 95% confidence intervals

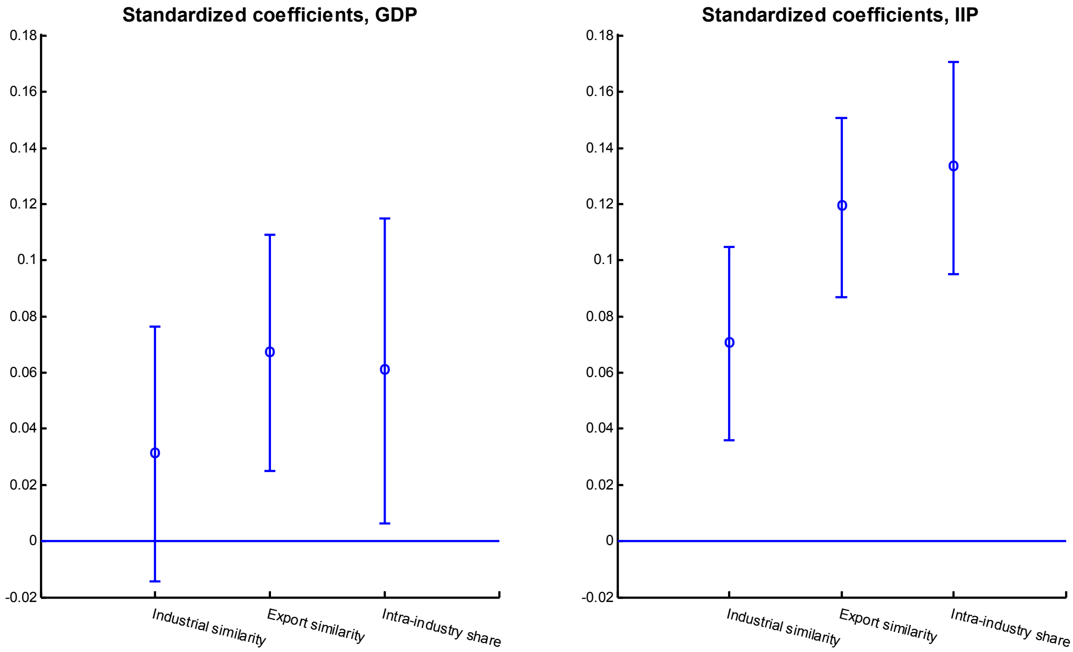


Figure 3.9 showed the economic significance of the determinants of synchronization, but this does not yet give an indication of the prospects for synchronization in the euro area. Table 3.6 examines this issue by looking at three scenarios. The first column shows the actual average correlation between EMU countries, the second shows the correlation predicted by the regression.[81] The last three columns show projected correlations according to three scenarios. The first scenario is cautious and assumes that the monetary union, with perfectly correlated monetary policy and no exchange rate variability, is the only difference compared to the 1970-2003 period. The other variables are set equal to the average for EMU countries over the period 1970-2003. The second scenario sets all other variables equal to the average for the period 1992-2003. The third scenario is the most speculative and assumes that (cyclically-adjusted)

[81] The intra-industry OLS regressions from Table 3.5 are used for the predication and projections. The predicted value is lower than the actual average since EMU countries have a correlation that is higher than the average in the full sample. Regression to the mean leads to the lower prediction.

fiscal policy will be perfectly correlated. As the table shows, each of the scenarios implies an economically significant, but not implausible, rise in the predicted correlation. The rise in the projected correlation from Scenario II relative to Scenario I shows that in the period between 1992 and 2003, the explanatory variables favoured higher synchronization. Part of this effect can be traced to more correlated monetary policy, fiscal policy and stock market returns. In addition, a rise in the average intra-industry share, from 40 percent between 1970 and 1981 to 52 percent after 1992, made a notable contribution. In comparison, export similarity also increased, but by less than the intra-industry share and industrial similarity decreased modestly. This confirms the importance of looking at trade-based measures of specialization and that based on those measures, specialization has actually decreased in recent decades. Note also that the range of projections, from 0.64 to 0.75, corresponds to the range of post-war average correlations of states within the U.S. from Table 3.2.

Table 3.6 Actual, predicted and projected output correlations between EMU countries based on the intra-industry regressions

	Actual average (1970-2003)	Predicted value (1970-2003)	Projections		
			Scenario I	Scenario II	Scenario III
GDP	0.62	0.58	0.65	0.71	0.74
Industrial production	0.63	0.59	0.64	0.70	0.75

Scenario I: correlation of monetary policy is 1, exchange rate variability is 0. All other variables are equal to the 1970-2003 average for EMU countries.

Scenario II: correlation of monetary policy is 1, exchange rate variability is 0. All other variables are equal to the 1992-2003 average for EMU countries.

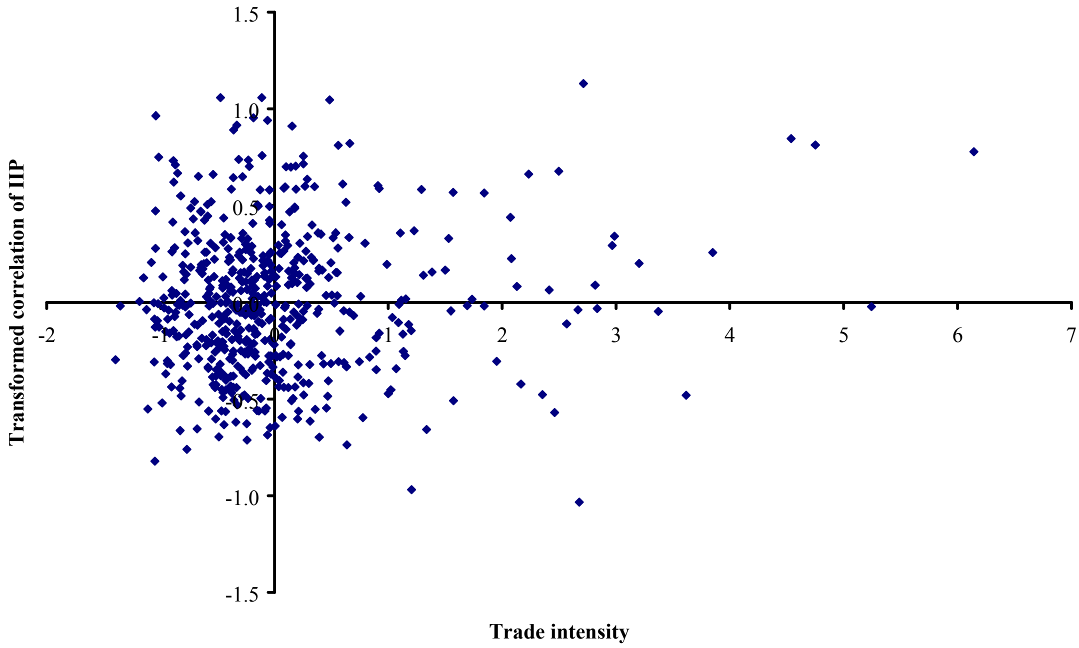
Scenario III: correlation of monetary policy is 1, exchange rate variability is 0 and correlation of fiscal policy is 1. All other variables are equal to the 1992-2003 average for EMU countries.

Predictions and projections are based on the intra-industry regressions from Table 3.5.

Sample heterogeneity and outliers

There are two potential problems with the OLS results. First of all, outlying observations may influence the results and second, the identified relationships may not be the same for different groups of observations. Figure 3.11 shows the residuals of the regression of business cycle correlation for industrial production on the control variables against the residuals of the regression of bilateral trade on these same control variables. This figure suggests that there are various observations that are quite far away from the bulk of the observations and these may drive the results. This section reports the estimation results using the Least Trimmed Squares (LTS) estimator of Rousseeuw (1984, 1985) to identify outlying observations. Furthermore, quantile regressions are used to examine sample heterogeneity.[82]

Figure 3.11 Scatter diagram of industrial production correlations and trade (after conditioning on other explanatory variables)



The basic principle of LTS is to fit the majority of the data, after which outliers may be identified as those points that lie far away from the robust fit. LTS typically minimizes the sum of squares over half the observations, the chosen half being the set that gives the smallest residual sum of squares. Although this method is particularly suited for identifying leverage points, it is not suited for inference. As proposed by Rousseeuw (1984), this can be resolved by using re-weighted least squares (RWLS). A simple, but effective, way is to give a weight of zero to all observations identified as outliers and a weight of one to all other observations (Sturm and De Haan, 2005).

Table 3.7 shows the results of the LTS/RWLS estimates. For comparison purposes, the OLS results of Table 3.5 are also shown. Overall, there are no large differences

[82] See Koenker and Basset (1978) for the seminal contribution or Koenker and Hallock (2001) for a non-technical overview.

between the OLS estimates and the robust estimates. However, there are exceptions. In the models for the GDP-based correlations, the bilateral trade coefficient loses significance in some specifications. This is quite remarkable, as almost all other variables remain significant at the 5% level. Still, in the models for the industrial production correlations, the significance of the trade variable increases. This suggests that in general, the effect of trade on business cycle synchronisation is not driven by outliers.

Table 3.7 The effect of trade on business cycle synchronization, OLS versus LTS/RWLS estimation

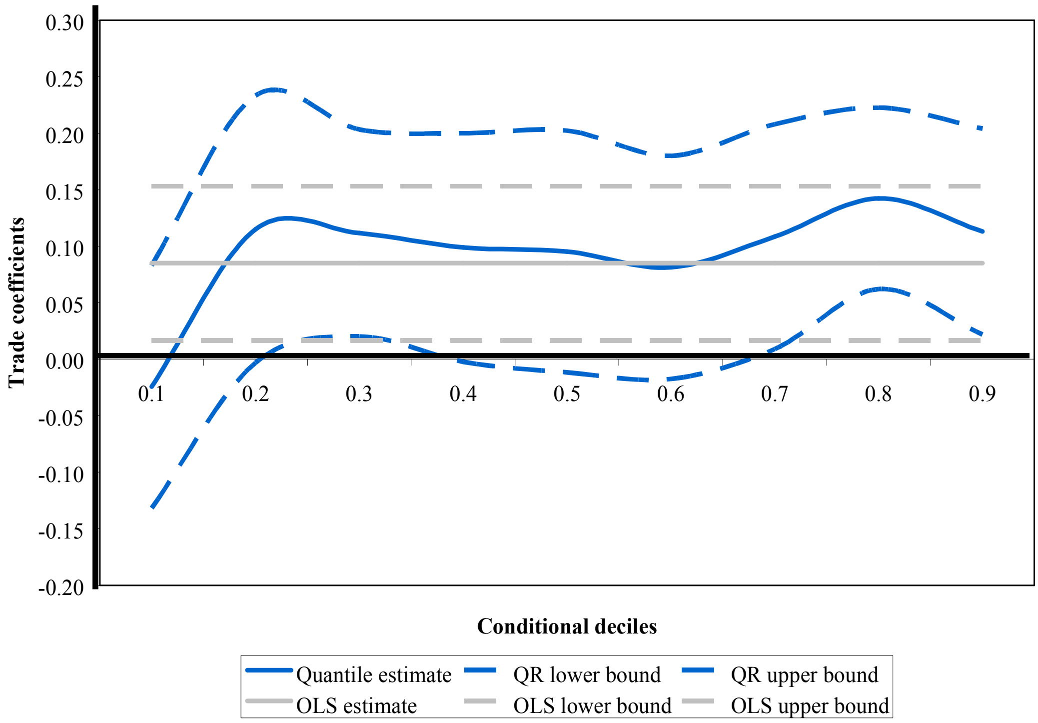
Specialisation measure:	*Industrial similarity*		*Export similarity*		*Share of intra-industry trade*	
GDP	OLS	LTS/RWLS	OLS	LTS/RWLS	OLS	LTS/RWLS
Trade	0.043*	0.044*	0.053*	0.033	0.044	0.022
	(0.020)	(0.020)	(0.021)	(0.018)	(0.023)	(0.020)
Specialisation measure	0.032	0.041*	0.064*	0.059*	0.346*	0.354*
	(0.024)	(0.021)	(0.021)	(0.018)	(0.159)	(0.122)
Correlation of short-term interest rates	0.239*	0.274*	0.124*	0.207*	0.129*	0.177*
	(0.055)	(0.050)	(0.057)	(0.045)	(0.057)	(0.045)
Correlation of cyclically-adjusted budget deficits	0.172*	0.191*	0.143*	0.161*	0.136*	0.16*
	(0.036)	(0.036)	(0.038)	(0.034)	(0.037)	(0.034)
Correlation of stock markets	0.308*	0.266*	0.214*	0.138*	0.225*	0.158*
	(0.080)	(0.068)	(0.065)	(0.051)	(0.064)	(0.051)
Exchange rate variability	-1.600*	-1.373*	-1.552*	-1.920*	-1.548*	-1.768*
	(0.483)	(0.416)	(0.460)	(0.392)	(0.458)	(0.393)
Industrial production						
Trade	0.080*	0.092*	0.069*	0.074*	0.043*	0.048*
	(0.021)	(0.017)	(0.019)	(0.015)	(0.021)	(0.016)
Specialisation measure	0.070*	0.056*	0.118*	0.136*	0.761*	0.838*
	(0.018)	(0.017)	(0.016)	(0.016)	(0.111)	(0.100)
Correlation of short-term interest rates	0.374*	0.392*	0.221*	0.267*	0.211*	0.268*
	(0.042)	(0.041)	(0.042)	(0.039)	(0.041)	(0.039)
Correlation of cyclically-adjusted budget deficits	0.125*	0.117*	0.157*	0.186*	0.143*	0.141*
	(0.034)	(0.032)	(0.030)	(0.030)	(0.030)	(0.029)
Correlation of stock markets	0.161*	0.223*	0.064	0.047	0.082	0.101*
	(0.060)	(0.057)	(0.052)	(0.044)	(0.050)	(0.043)

Notes: The dependent variable is the transformed output correlation. * denotes coefficient significantly different from zero at 5% level. Heteroscedasticity-consistent standard errors are shown in parentheses. LTS/RWLS shows regressions robust for outliers.

Quantile regression is an appropriate tool to address sample heterogeneity as shown by Koenker and Basset (1978). OLS focuses on the mean of the dependent variable given the explanatory variables. Quantile regressions are used to analyze other parts of the conditional distribution, such as the (conditional) median or specific deciles. The difference between the OLS and the median regression can help clarify this. In OLS, the sum of squared residuals is minimized, while for the median regression, the sum of absolute residuals is minimized. Regressions for other deciles can be run by giving a greater weight to positive or negative residuals. In order to increase the degrees of freedom, the sample period 1970-2003 is divided into eight periods of uniform lengths after which the same regressions as for Table 3.5 are run.

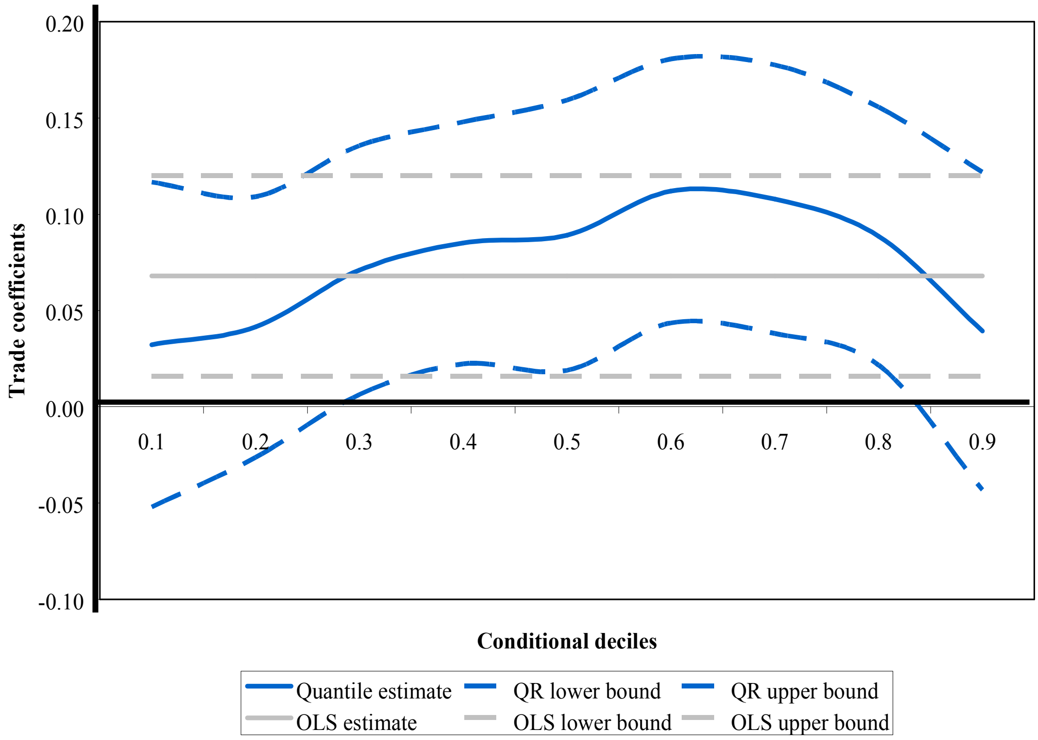
Figures 3.12 and 3.13 show the estimated coefficients of the trade intensity variable for each decile, using the model in which intra-industry trade is used as specialization measure.[83] It follows that the relationship between the correlation of business cycles and bilateral trade is fairly robust across deciles. The estimates for each conditional decile are almost always significant at the 5% significance level. More importantly, the figures show that the quantile regression estimates are very similar to the OLS estimates and almost always lie within the 95% confidence band of the OLS estimates. This indicates that the relationship between business cycle correlations and bilateral trade does not differ across the sample.

Figure 3.12 Quantile regression estimates of the effect of trade on synchronization, GDP correlations



[83] For brevity, only the estimates across deciles for bilateral trade are shown.

Figure 3.13 Quantile regression estimates of the effect of trade on synchronization, industrial production correlations



3.6 Concluding remarks

One of the main long-run challenges to the euro is the possible lack of similarity of business cycles in the member countries. If the degree of synchronization is low, the ECB's common monetary policy will not be suitable for all countries. In other words there is a risk is that 'one size does not fit all'. Monetary policy will be too restrictive for countries that face a recession while the rest of the euro area flourishes or too accommodating for economies that perform better than the average.

Since the late 1970s, monetary integration within Europe has increased steadily with the introduction of the euro as the high mark. However, synchronization is not solely determined by monetary integration as synchronization within Europe has fluctuated over time. Furthermore, the dispersion around the mean is quite sizeable, suggesting a great degree of heterogeneity. Still, since the mid-1980s, synchronization between EMU countries has been higher on average than between other countries.

The experience of the U.S. suggests that even decades of monetary union is no guarantee of perfect synchronization. The average correlation between state cycles and the aggregate cycle is somewhat higher than among EMU countries, but not much. The dispersion of cyclical correlations is notably smaller though, with fewer negative correlations between states. Synchronization between states also varies over time, and this variation is larger than between EMU countries. An important factor in this variation seems to be the aggregate U.S. business cycle. In periods of great volatility, such as the Great Depression, the national cycle plays a dominant role and synchronization is high. In contrast, the volatility of the U.S. economy has been relatively low in the past two decades, resulting in lower levels of synchronization.

Comparing patterns of synchronization over time is useful to capture broad trends, but for specific policy recommendations, the determinants of synchronization need to be examined. A set of robust explanatory variables was identified from a large set of variables using Extreme Bounds Analysis (EBA). The robust variables include trade intensity, measures of specialization, financial integration as given by the correlation of stock market returns, the similarity of monetary and fiscal policy and exchange rate variability. The resulting multivariate model is able to account for the endogeneity of trade. The main problem in estimating the effect of trade on synchronization is that other policy-related and structural variables affect both trade and synchronization. It turns out that once the variables identified using EBA are added to the regression, the hypothesis of OLS consistency is no longer rejected. This suggests that the endogeneity of trade is no longer a major problem.

In the multivariate model, trade is still an important explanatory variable, but in terms of economic significance, the other explanatory variables are equally important. Projections of future output correlations between EMU countries suggest that synchronization is likely to increase to similar levels as between U.S. states. The main uncertainties in these projections are the degree of coordination of fiscal policy and the development of specialization. Resistance against the rules of the Stability and Growth Pact suggests that the appetite for fiscal policy coordination is limited. It should be noted though that strict adherence to deficit limits is not crucial for synchronization. Instead, the main factor is the similarity of policy. So a unilateral spending spree is likely to reduce synchronization, but a large deficit in response to adverse cyclical developments is unlikely to have such an effect.

The future direction of specialization is harder to gauge. In part, this is because different specialization measures show different patterns in Europe. On the one hand, there has been a modest decrease in industrial similarity in recent decades, but on the other hand, both the similarity of export bundles and the intra-industry share have increased. The U.S. experience suggests that the trade-based measures may be most relevant. Kim (1995) showed that the industrial structure of U.S. regions has become more homogenous in the past decades due to more mobile production factors. As Europe has been working towards a single market for capital and labour, specialization could decrease further, increasing synchronization. This issue might also become more important as other evidence for the U.S. suggests that the national cycle has become less volatile, leading to a larger effect of region-specific and industry-specific shocks on synchronization.[84] If similar developments occur in Europe, changes in specialization patterns will become even more important in determining future synchronization.

These uncertainties strengthen the case for more flexibility, following De Grauwe and Mongelli (2005). Specifically, it should be easier for Europeans to take jobs in other countries. Blanchard and Katz (1992) show that economic shocks in U.S. states induce notable migration out of that state in addition to higher unemployment and lower wages. In contrast, Puhani (2001) argues that even within a number of European countries, labour mobility is not a very effective adjustment mechanism. Currently, there are not just language and cultural barriers, but, for example, pension and insurance systems are also not compatible. Reforms aimed at reducing these barriers are likely to decrease the degree specialization as well as making it easier for countries to absorb asymmetric shocks. Both developments would reduce the costs of having a common currency. In addition, as the next chapter will argue, more flexible labour markets will also stimulate productivity growth.

[84] See Partridge and Rickman (2005). See also Clark and Shin (2000) for more on identifying different types of shocks.

Appendix 3.A Extreme bounds analysis

Appendix Table 3.1 Robustness of potential explanatory variables for synchronization

Variable:	Source:	Suggested by:	Robust in model for:	
			GDP correlation	*IIP correlation*
Correlation of short-term interest rates	IMF, International Financial Statistics (IFS)	Otto *et al.* (2001)	Yes	Yes
Correlation of cyclically-adjusted budget deficits	OECD Economic Outlook (vol. 76)	Camacho *et al.* (2005)	Yes	Yes
Correlation of stock market returns	IFS	Otto *et al.* (2001)	Yes	Yes
Absolute difference in net foreign asset positions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Capital account restrictions	Milesi-Feretti and IMF	Imbs (2004)	No	No
Industrial similarity	GGDC 60-industry database	Imbs (2004)	No	Yes
Export similarity	Feenstra *et al.* (2005)	Baxter and Kouparitsas (2004)	Yes	Yes
Share of intra-industry trade (IIT)	Feenstra *et al.* (2005)		Yes	Yes
Exchange rate variability	IFS	Otto et al. (2001)	Yes	No
Arable land difference	WDI	Baxter and Kouparitsas (2004)	No	No
Human capital difference, secondary education	OECD Labour Force Statistics	Baxter and Kouparitsas (2004)	No	No
Human capital difference, tertiary education	OECD Labour Force Statistics	Baxter and Kouparitsas (2004)	No	No
Physical capital difference	GGDC Total Economy Growth Accounting Database	Baxter and Kouparitsas (2004)	No	No
Import similarity	Feenstra *et al.* (2005)	Baxter and Kouparitsas (2004)	No	No
Average openness	IFS & GGDC Total Economy Database	Baxter and Kouparitsas (2004)	No	No
Relative financial structure credit/stock	Beck et al. (1999)	Artis (2003)	No	No
Relative labour productivity level	GGDC Total Economy Database	Baxter and Kouparitsas (2004)	No	No
Correlation of inflation rates	IFS	Camacho *et al.* (2005)	No	No
Average oil import share	World Bank, World Development Indicators (WDI)	Artis (2003)	No	No
Difference in national savings ratio	OECD National Accounts	Camacho *et al.* (2005)	No	No

Note: A more detailed description of the variables and sources, as well as the data is available at www.rug.nl/economics/inklaarrc

The Extreme Bounds Analysis (EBA) as suggested by Leamer (1983) and Levine and Renelt (1992) is used to determine the list of variables to be included in the structural model outlined in the main text. EBA has been widely used in the economic growth literature.[85] Baxter and Kouparitsas (2004) also use this methodology (using a different set of countries and a more limited set of potential explanatory variables than in the present analysis) to examine which variables are robustly related to business cycle synchronization. The EBA can be exemplified as follows. Equations of the following general form are estimated:

(3.A1) $C = \alpha M + \beta F + \gamma Z + u$,

where C is the dependent variable (output correlation); M is a vector of 'standard' explanatory variables; F is the variable of interest; Z is a vector of up to three (Levine and Renelt, 1992) possible additional explanatory variables, which according to the literature may be related to the dependent variable; and u is an error term. In this analysis only trade intensity is included in the M vector. As explained in the main text, the various proxies for financial integration and specialization are not considered simultaneously. Following Sala-i-Martin (1997), the criterion for the robustness of the sign of the coefficient is the fraction of the cumulative distribution function lying on one side of zero (CDF(0)). In addition, the percentage of the regressions in which the coefficient of the variable of interest differs significantly from zero is used to distinguish robust variables. Following Sturm and De Haan (2005), a variable is considered to be robust if the CDF(0) test statistic is larger than 0.95 and if the variable has a significant coefficient (at the 5% significance level) in 90% of all regressions.

[85] See Sturm and De Haan (2005) for a further discussion

Chapter 4 Productivity growth and ICT use[86]

4.1 Introduction

Oer the past decade, labour productivity growth in Europe has fallen behind growth rates in the United States, reversing the pattern of growth since the Second World War. Much has been written about why U.S. productivity growth accelerated and whether the pace of growth is sustainable.[87] However, by now the U.S. has outpaced European productivity growth for nearly a decade since 1995 and U.S. growth shows little sign of letting up.

Among the potential explanations for this growth gap, a prominent candidate is the slower uptake and less productive use of Information and Communication Technologies (ICT) in Europe. Over the past few decades, ICT has become increasingly pervasive in modern societies. Two main developments have spurred this uptake of new technology. First of all, rapid technological progress has driven down the cost of ICT goods and second, the number of applications of ICT has multiplied over the years, enabled by this technological progress. These twin developments have reinforced each other, making ICT a general purpose technology like steam and electricity.[88]

As a result of these characteristics, one would expect ICT to have an impact on labour productivity growth. Indeed, there are three channels through which an ICT impact may occur, namely from the production of ICT goods and services, investment in ICT and spillovers from the use of ICT. Total factor productivity (TFP) growth in ICT producing industries will quite naturally contribute to aggregate TFP growth and hence labour productivity growth. In a neo-classical framework, the contribution from ICT investment is also well defined: firms will invest in ICT up to the point where further output gains are equal to the marginal cost of the investment. This way the

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[86] This chapter builds on van Ark, Inklaar and McGuckin (2003a, b) and Inklaar, O'Mahony and Timmer (2005). See the acknowledgements for further details.

[87] See, for example, Jorgenson and Stiroh (2000) and Oliner and Sichel (2000) for relatively optimistic early assessments, Gordon (2000) for a more sceptical argument, and Gordon (2003) and The Economist (2003) for a retrospective on some of these arguments.

[88] For an economic growth model along these lines, see Bresnahan and Trajtenberg (1995).

contribution from growth in ICT capital per hour worked to labour productivity growth can be quantified. The final channel is the hardest to measure and also raises conceptual issues. The underlying idea is that ICT enables the introduction of new organizational models and other innovations. So although new ICT investment goods are standard products, they enable firms to innovate and accumulate firm-specific capital (see e.g. Brynjolfsson and Hitt, 2000 and OECD, 2004). For example, a network of off-the-shelf computers, scanners and databases can be combined into a system that tracks and replenishes inventories and gives insight into patterns of customer purchases. Insofar as these innovations yield additional output gains, they will show up as additional total factor productivity growth in ICT using industries and may be labelled as spillovers. To be precise, if the organizational and other intangible investments were properly accounted for, these ‘spillovers’ should disappear.

The main question this chapter poses is to what extent Europe has failed to exploit the growth potential of ICT. Specifically, slower ICT investment could be a reflection of a time lag relative to the U.S. or indicate a more structural failure to exploit new technologies. A time lag may be due to the more fragmented nature of the European market. The greater scale of the U.S. market can make certain investments more profitable early on, while ICT prices have to fall further before it is profitable in Europe too. On the other hand, ICT investment in Europe might permanently lag the U.S., because regulations hold back the diffusion of complementary innovations. For example, young, innovative firms may face obstacles to fast growth, such as restrictive land-use regulations. This in turn reduces the incentives for incumbent firms to innovate too.

With the availability of industry data on ICT and productivity growth for the U.S. and several European countries, the link between productivity and ICT can be investigated in detail. This chapter argues that the declining rate of productivity growth in Europe may be a reflection of a slow transition process towards so-called “soft savings” from ICT usage, in particular in market services. These follow the earlier “hard savings” which could be immediately obtained from ICT investment. For example, the earliest application of barcode scanning in supermarkets was to speed up check-out. Along the lines of the literature on general purpose technologies, the results suggest that “soft savings” require investments in intangible capital and organizational innovations, which are most likely to be important in market services. The market services sector is the biggest investor in ICT and is also most dependent on additional innovations to produce new ICT-related services. For example, in addition to speedier check-out, barcodes can be used reorganize the supply chain to take advantage of the increased information on customer purchases, but this is much less straightforward. The European institutional environment, reflected in its labour and product market institutions, tends to hold up the structural adjustment process in Europe and inhibits the reallocation of resources to their most productive uses. The European economic environment creates too little room for good firms to excel and for failing firms to exit the market.

This chapter begins with a presentation of the macroeconomic evidence on the contribution of ICT to productivity growth, using a growth accounting approach. Next, the labour productivity growth gap between the EU-15 and the U.S. is examined at the industry level. This analysis shows that the key to understanding the difference in growth between both economies can be found in the differential growth performance of market services (Section 4.3). Section 4.4 shows that market services is also the most intensive ICT using sector in both the American and European economies. Due to the scarcity of data on ICT investment for individual industries, a more detailed analysis of ICT intensity and TFP growth at the industry level is restricted to four major European countries (France, Germany, the Netherlands and the UK) and the U.S. (Section 4.5). This section delves more deeply into the evidence and implications of the relationship between ICT and TFP growth. The concluding section focuses on the concepts of "hard" and "soft" savings from ICT, on the one hand, and the relation to the competitive market environment in Europe and the U.S. on the other hand.

4.2 ICT and aggregate growth

Economists have been looking for an impact of ICT on growth for almost two decades, but until recently, these researchers spent most of their time explaining why this impact was lacking.[89] It was only with the work of Jorgenson and Stiroh (2000) and Oliner and Sichel (2000) that the impact of ICT on growth in the United States showed up strongly in the data, although at that time Gordon (2000) argued that part of the effect reflected cyclical instead of structural factors. In earlier years, part of the

[89] This is exemplified by Solow's (1987) quote that computers can be seen everywhere except in the productivity statistics. See also Oliner and Sichel (1994) and Triplett (1999).

reason why ICT contributed little to labour productivity growth was that ICT capital was only a small percentage of the total capital stock (Oliner and Sichel, 1994). Improvements in the measurement of computer and semiconductor prices have also been important in revealing the effects of ICT on labour productivity growth (Jorgenson, 2001). Since the work of Jorgenson and Stiroh (2000) and Oliner and Sichel (2000) it has become an established fact that a significant part of the acceleration in labour productivity growth after 1995 in the United States can be attributed to the production and use of ICT.[90]

The United States is not the only country where ICT is thought to have played an important role in stimulating productivity growth. Indeed, from the mid-1990s onwards, labour productivity growth in Australia also accelerated strongly, with important contributions from faster ICT investment and TFP growth (see Parham, Roberts and Sun, 2001). Australia is an interesting case since it does not have an important ICT producing sector, so productivity gains from ICT can mostly be traced to either the investment or the spillover channel.

In Europe, evidence on the impact of ICT on productivity has been much harder to come by, see for example the review of van Ark (2000). Early work by Schreyer (2000) and Daveri (2000, 2002) relied heavily on private data sources to estimate ICT investment. The consistency of these sources with investment data from the National Accounts was quite questionable though. Colecchia and Schreyer (2002) were the first to collect genuine ICT investment data for a limited number of countries, but it was not until the work of van Ark *et al.* (2002) that ICT investment data was collected for nearly all EU member countries.[91]

Data sources and methods

To analyze the contribution of ICT to growth, a theoretical framework is needed. Assume that gross domestic product (Y) is produced from factor inputs X, consisting of ICT capital services (K_{ICT}), non-ICT capital services (K_N) and labour services (L).

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[90] In extensions of their earlier work, Jorgenson, Ho and Stiroh (2005) and Oliner and Sichel (2002) broadly confirm their findings. Gordon, one of the most vocal academic critics a few years ago in his 2000 article, has also come round to this position in more recent work (Gordon, 2003). It should be noted though that recent revisions by the U.S. Bureau of Economic Analysis (BEA) have reduced U.S. GDP growth before 2000, making the 1995-2000 less exceptional in retrospect.

[91] In addition, a number of studies have looked at the impact of ICT investment in individual countries. See van Ark (2002) for an overview.

Total factor productivity (A) is represented as a Hicks-neutral augmentation of the aggregate inputs. The aggregate production function has the following general form:

(4.1) $$Y = AX(L, K_N, K_{ICT}).$$

In this framework, total factor productivity measures technical change and is equal to output growth after accounting for the contributions of all inputs. These contributions can be estimated econometrically, but a common (non-parametric) method to analyze the sources of growth is the growth accounting framework (Solow 1957, Jorgenson and Griliches, 1967). Under the assumption of cost-minimizing producers, competitive factor markets, well-measured inputs and output, and constant returns to scale, total factor productivity (TFP) growth also measures technical change and can be calculated non-parametrically.

However, it is unlikely that all assumptions are fully satisfied and growth accounting has often been criticized because of this. In general, as for example Hulten (2001) argues, TFP is a residual that measures shifts in the production function. These shifts can occur for a variety of reasons, such as technical change, but it can also capture, for example, returns to scale. The main advantage of growth accounting is that it provides a simple and consistent method to account for the contributions from factors that can easily be identified, namely capital and labour.[92] This greatly simplifies the task of testing for deviations from the standard assumptions and dissecting the TFP residual into harder to measure components such as measurement errors, scale economies or spillovers from research and development (R&D). Later in this chapter and in Chapter 5, some of the key growth accounting assumptions will be tested and based on those results, no clear alternative assumptions seem warranted.

The growth accounts are implemented by assuming a translog production function, which only mildly restricts the production function of equation (4.1).[93] As Diewert (1976) showed, the (non-parametric) Törnqvist index can be used to represent such a translog function.[94] A Törnqvist index for the growth of aggregate factor inputs from t to t+1 is equal to the weighted average of the growth in each of the individual inputs, where the weight is equal to the share of each input in total

[92] At the industry level, intermediate inputs also become important; see Chapter 5.
[93] Specifically, the translog function is a second order approximation to an arbitrary, twice continuously differentiable linearly homogenous function; see Christensen, Jorgenson and Lau (1973).
[94] Or to be precise, the Törnqvist index is exact for the translog function.

income, averaged over periods t and t+1. TFP growth can then be derived as the growth of output minus the growth of aggregate inputs:

(4.2) $$\Delta \ln A = \Delta \ln Y - \bar{v}_L \Delta \ln L - \bar{v}_N \Delta \ln K_N - \bar{v}_{ICT} \Delta \ln K_{ICT},$$

where Δ refers to first differences and $\bar{v}$'s denote the two-period average shares in total factor income. Because of constant returns to scale: $\bar{v}_L + \bar{v}_N + \bar{v}_{ICT} = 1$, when calculating these shares as a percentage of GDP. By rearranging equation (4.2), average labour productivity growth, defined as $y = Y/L$, can be decomposed into the ratio of capital services to hours worked, $k = K/L$, and TFP growth. Another useful distinction can be made between TFP originating in manufacturing industries producing ICT goods (A_{prod}) and other industries (A_{other})

(4.3) $$\Delta \ln y = \bar{v}_N \Delta \ln k_N + \bar{v}_{ICT} \Delta \ln k_{ICT} + \Delta \ln A_{prod} + \Delta \ln A_{other}.$$

The estimates on the comparative growth performance of the EU-15 and the U.S. presented here are an update from earlier work by Timmer *et al.* (2003) and Timmer and van Ark (2005). The estimates on investment, capital services, labour input and GDP are updated from 2001 to 2004.[95] Data on investment, GDP and labour compensation are typically derived from the national accounts. However, substantial additional work was required to construct separate investment time series for three ICT assets (office and computing equipment, communication equipment, and software) as well as three non-ICT assets (non-ICT equipment, transport equipment and non-residential structures).[96]

To obtain separate TFP estimates at the macro level for ICT-production industries, the assumption is made that TFP growth rates for ICT-production (office, accounting and computing equipment, communication equipment and electronic components manufacturing) in the U.S. also apply to the European countries. To measure the ICT industry contributions to total factor productivity growth, Domar weights for the individual countries were used.[97]

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[95] Many thanks go to Gerard Ypma, who constructed much of the data used in this section.

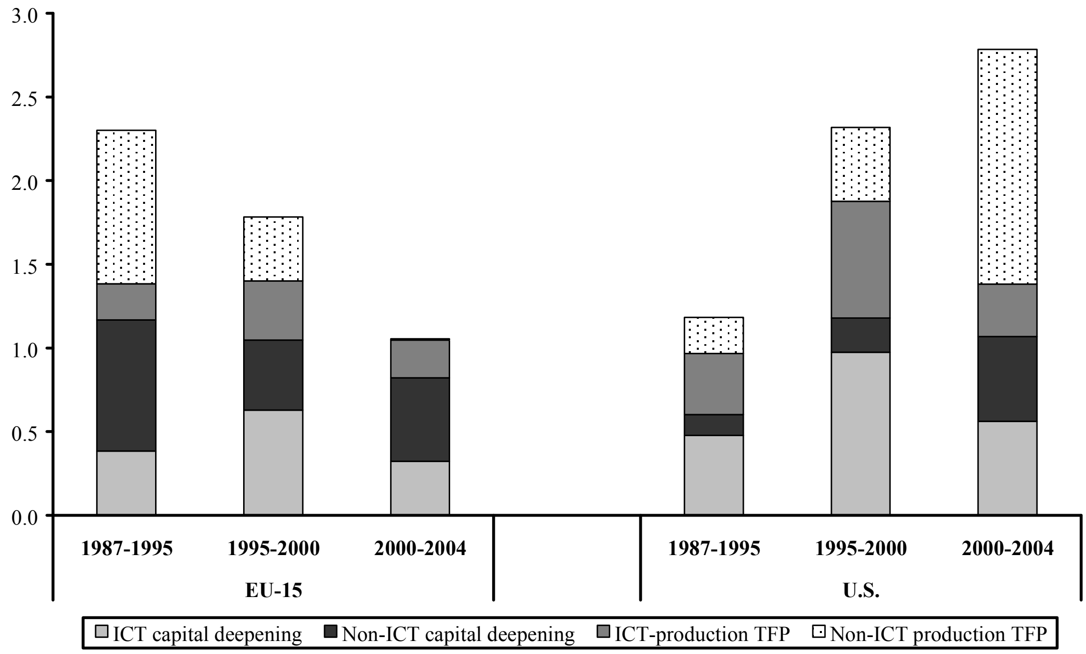
[96] See http://www.ggdc.net/dseries/growth-accounting.html for further details on sources and methods and underlying data. The methodology to obtain the ICT investment series, the deflators for ICT series (which are essentially derived from U.S. hedonic price deflators for ICT) and the capital services method can be obtained from Timmer, Ypma and van Ark (2004) and Timmer and van Ark (2005). Section 4.4 also discusses capital services measurement in more detail.

[97] See Appendix 4.A for further details.

Sources of aggregate labour productivity growth

Figure 4.1 summarizes the main findings for the EU-15 and the U.S. for the periods 1987-1995, 1995-2000 and 2000-2004. The chart shows a decomposition of labour productivity growth into the effects of ICT capital deepening, TFP growth from ICT-producing industries, non-ICT capital deepening and TFP growth other than that from ICT production. The main findings are that the EU-15 as a whole has been lagging behind the U.S. in terms of ICT capital deepening in each period. Both the EU-15 and the U.S. show a strong acceleration in ICT capital deepening during the late 1990s. However, this investment boom was mostly transitory, with ICT capital deepening returning to pre-1995 levels after 2000 in both the EU-15 and the U.S. Since 2000 though, U.S. labour productivity accelerated further, while the EU-15 suffered additional slowdown. This divergence between the Europe and America can mostly be traced to higher TFP growth outside the ICT producing sector. In Europe, TFP growth outside ICT production was effectively zero after 2000, while in the U.S. “non-ICT production” TFP growth added almost 1.5 percentage points to labour productivity growth. This might be because Europe is not generating ICT spillovers, while the U.S. is, but other causes may be important too.[98]

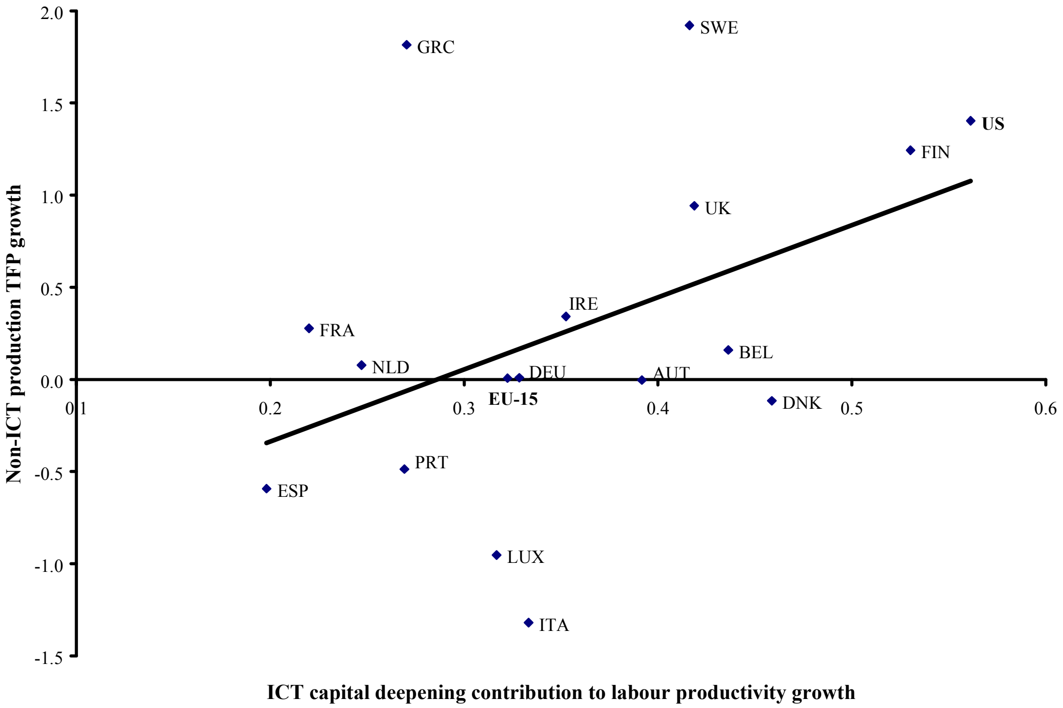
Figure 4.1 Sources of labour productivity growth, EU-15 and U.S., 1987-2004



[98] Estimates for individual countries can be obtained from Timmer, *et al.* (2003). Although there is much variation in TFP not related to ICT, growth is generally slower after 1995, with the exception of Sweden and the United Kingdom. See also http://www.ggdc.net/dseries/growth-accounting.html.

"Non-ICT production" TFP growth may include an element of ICT spillovers. An impressionistic way of getting at possible spillover effects at the macro-level is to relate the contribution from ICT capital deepening to "non-ICT production" TFP growth for the period 2000-2004 (Figure 4.2). This scatter plot shows a very suggestive positive relationship between these two variables, with countries like the U.S., the UK, Finland and Sweden combining high ICT investment and high non-ICT TFP growth, and countries like France, Italy and Spain show the opposite.

Figure 4.2 ICT contribution and non-ICT TFP growth, 2000-2004

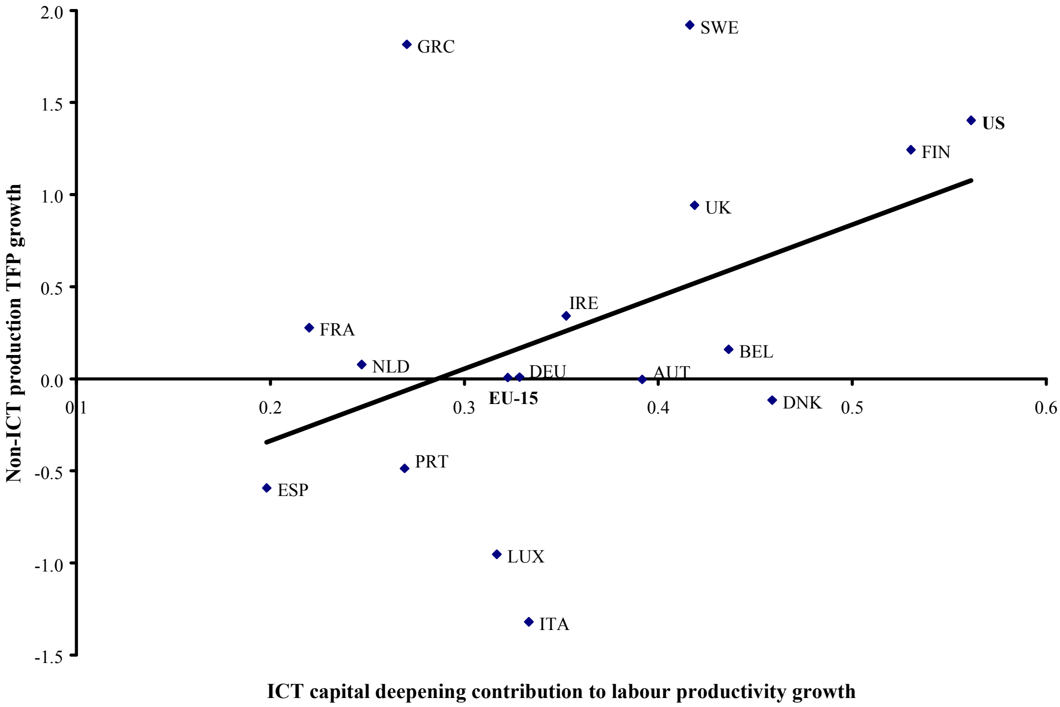


Of course, Figure 4.2 is only a simple, though suggestive, scatter plot. It is therefore useful to test the scope of this finding. The first concern is whether this relationship is stable for different periods and the second is whether the relationship can still be seen when controlling for initial TFP levels.[99] Figure 4.3 already shows that for the period between 1995 and 2000, no relationship can be found. Further answers are provided in Table 4.1, which shows the parameters for the period 1995-2000 in addition to 2000-2004. Furthermore, regressions both with and without the

[99] See Appendix 4.B to this chapter for a description of the construction of these TFP levels.

initial TFP level are shown and with total TFP growth and non-ICT production TFP growth as dependent variables.[100]

Figure 4.3 ICT contribution and non-ICT TFP growth, 1995-2000



As the table shows, a significant positive relationship can only be discerned for the 2000-2004 period and only when the initial TFP level is included as a control variable. The initial TFP level is only significant when non-ICT TFP growth is used as the dependent variable. Most important to note is that for the 1995-2000 period, the ICT coefficient is close to zero, even though U.S. growth had started to accelerate by then. Similar regressions were run for each available starting year, averaging over different numbers of years, but a significant ICT effect appears only for periods that include years after 1998.

[100] The initial level is defined here as the TFP level at the start of the relevant period. So for the 1995-2000 period, the 1995 TFP level is included.

Table 4.1 The cross-country relationship between ICT capital deepening and TFP growth for the EU-15 and the U.S.

	1995-2000		2000-2004	
Dependent variable: TFP growth				
ICT contribution	0.19	0.26	4.79	4.77*
	(1.26)	(1.26)	(2.31)	(2.16)
TFP level		-0.02		-0.02
		(0.02)		(0.01)
Dependent variable: Non-ICT TFP growth				
ICT contribution	-0.14	-0.10	3.91	3.88*
	(0.90)	(0.90)	(2.05)	(1.79)
TFP level		-0.01		-0.03*
		(0.01)		(0.01)

Notes: Cross-country regressions with TFP growth as the dependent variable and the contribution from ICT capital deepening and the initial TFP level as explanatory variables. The initial TFP level is defined as the level at the start of the period, so the 1995 level for the 1995-2000 period. * denotes significantly different from zero at the 5% level. Standard errors are in parentheses.

The results from Table 4.1 show that relying only on aggregate data does not provide robust results. The aggregate analysis severely limits the number of observations, so convincing statistical evidence is difficult to obtain. Another reason for caution is that there are many more variables that potentially affect TFP growth differences between countries such as, for example, differences in market structure and flexibility of product, labour and capital markets between countries. Thirdly, with declining aggregate TFP growth in most European countries it is hard to interpret this evidence as a sign of increased spillovers compared to the period before 2000. Indeed the significant relationship since 2000 has mainly occurred because countries with lower ICT investment, such as Italy, Spain and Portugal, have been showing slower TFP growth rather than from accelerations in countries with rapid ICT investment. This might at best imply that some countries have had more trouble in combining ICT with other growth-enhancing sources than others. Without TFP growth estimates for individual industries there is no good way of identifying such spillovers, as the aggregate TFP residual may include a whole range of unmeasured contributions (or detractions) to output growth which are difficult to distinguish at aggregate level. Hence the remainder of this chapter focuses on industry estimates of labour productivity and total factor productivity growth.

4.3 Industry contributions to labour productivity growth

As discussed in the introduction to this chapter, we would like to supplement the aggregate figures presented above with estimates of TFP growth for individual industries. Only then it becomes possible to see which industries are heavy ICT investors and whether these industries have higher TFP growth. This can help determine whether ICT spillovers are an important source of growth differences between Europe and the United States. At this time such estimates are only available on a comparable basis for 4 major European countries (France, Germany, the Netherlands, the UK) and the U.S., which will be discussed in Section 4.5. In the absence of industry-level growth accounts for all EU-15 countries, it is useful to first look at the labour productivity growth performance by industry for the EU-15.

The 60-industry database of the Groningen Growth and Development Centre (GGDC, 2005b) contains data for the period 1979-2003 on output and employment in 56 industries for all EU-15 countries, the United States and several other OECD countries. This database draws heavily on National Accounts, either as compiled in the OECD STAN database or directly from national sources, supplemented with information from industry censuses and surveys and labour force surveys.[101] For the analysis in the remainder of this chapter, we focus on the market economy, excluding non-market services from the industry data. The measurement of output for non-market services, such as health and education, is very problematic and might affect the aggregate results.[102]

Contribution and decomposition analysis

To determine the contribution of individual industries to aggregate growth, a decomposition method suggested by Stiroh (2002b) is used. This method is akin to the shift-share analysis that was used in earlier work (e.g. van Ark, Inklaar and McGuckin, 2003a). Define labour productivity growth as the difference between the growth of value added at constant prices and the growth of total hours worked:

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[101] The most recent dataset as well as more extensive documentation can be downloaded from www.ggdc.net. Chapter VII of O'Mahony and van Ark (2003) provides a detailed overview of methodological choices, such as the aggregation procedure and the use of harmonized U.S. deflators for ICT manufacturing industries.

[102] In addition, the real estate industry is excluded as most of the output in this industry consists of imputed housing rents.

(4.4) $$\Delta \ln y = \Delta \ln Y - \Delta \ln H .$$

As Stiroh (2002b) shows, aggregate labour productivity growth can be written as:

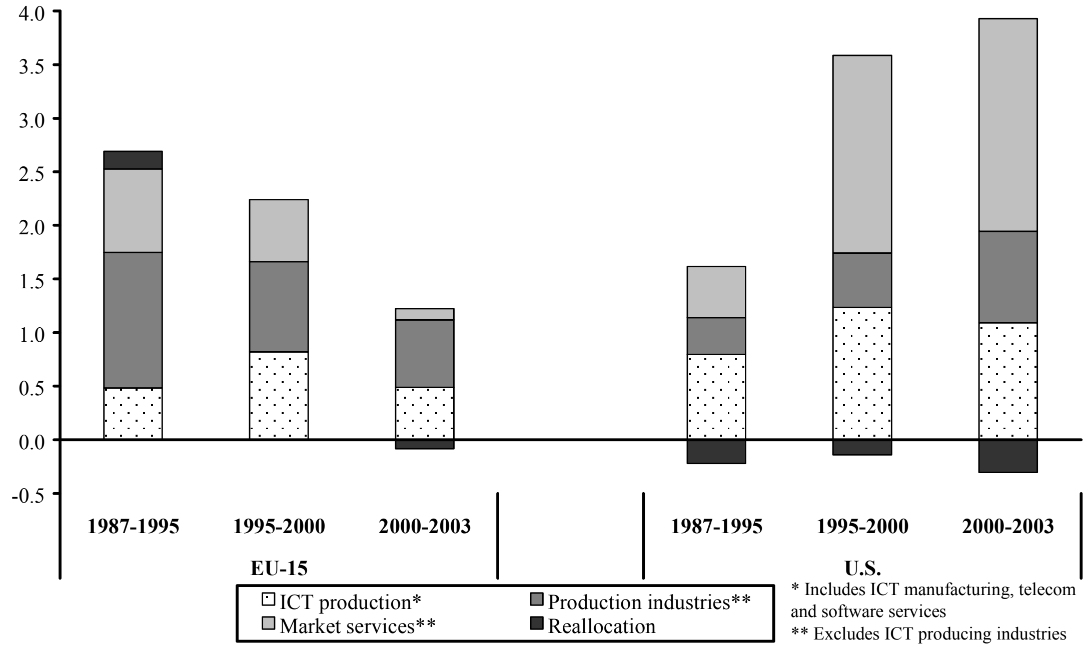
(4.5) $$\Delta \ln y = \sum_i \overline{w}_i \Delta \ln y_i + \left(\sum_i \overline{w}_i \Delta \ln H_i - \Delta \ln \sum_i H_i \right) = \sum_i \overline{w}_i \Delta \ln y_i + R .$$

In equation (4.5), w_i is the share of industry i in total value added and a bar over a variable denotes the two-period average.[103] Aggregate labour productivity growth is the weighted sum of industry productivity growth plus a reallocation term R. This reallocation term gives the differences between the output-weighted growth of hours and (roughly) the employment-weighted growth of hours (see Appendix 4.C for further discussion). If this term is positive it implies that, industries where the output share is larger than the employment share show faster employment growth than industries where the reverse is true. In other words, the reallocation term is positive if employment shifts towards industries with high productivity levels.

Figure 4.3 shows the contributions to market economy labour productivity growth from the main industry groups for Europe and the U.S.[104] The figure makes clear that the resurgence of U.S. growth after 1995 is not principally due to stronger growth in ICT producing industries. Instead, the performance of market services is the key to understanding the acceleration of U.S. growth.[105] For the 1995-2000 period, it was already quite striking how market services made a much larger contribution to labour productivity growth in the U.S. than in Europe. However, after 2000 the gap widened even more: while in the EU-15 market services added only 0.10 percentage points to growth, in the U.S. this sector made up almost 2 percentage points of overall growth in the market economy.

[103] This is based on a Törnqvist index of industry outputs. Since most statistical offices use different indexes, such as the Laspeyres or Fisher, the aggregate results will not be fully completely comparable to those published in the National Accounts. However, statistical offices are increasingly using so-called 'chained' indexes, with annually changing weights, so the differences will be limited in practice.
[104] The set of ICT producing industries is very close to the OECD (2002b) definition.
[105] Stiroh (2002b) already made a similar argument.

Figure 4.4 Contributions by industry groups to market economy labour productivity growth, EU-15 and U.S. 1987-2003



However, the market services sector is quite heterogeneous, including both florists and accountants, so it is useful to see which industries have mostly contributed to the difference in contribution. A first step is to simply calculate the difference in contribution of each industry: $\overline{w}_i^{US}\Delta\ln y_i^{US} - \overline{w}_i^{EU}\Delta\ln y_i^{EU}$. Summing across industries and adding the difference in the reallocation term then gives the difference in aggregate productivity growth. It can be interesting though to move beyond this straightforward expression and decompose the difference in industry contributions into an effect due to different output shares between the two regions and an effect due to different productivity growth rates:[106]

$$(4.6)\quad \frac{1}{2}\left(\Delta\ln y_i^{US} + \Delta\ln y_i^{EU}\right)\left(\overline{w}_i^{US} - \overline{w}_i^{EU}\right) + \frac{1}{2}\left(\overline{w}_i^{US} + \overline{w}_i^{EU}\right)\left(\Delta\ln y_i^{US} - \Delta\ln y_i^{EU}\right).$$

The first term in equation (4.6) weighs the difference in value added shares by the average productivity growth rates and is referred to as the *share effect (share_eff)*. The second term weighs the difference in labour productivity growth rates by the average value added share and is the *productivity growth effect (prodty_eff)*. The difference in aggregate productivity growth rates can then be written as:

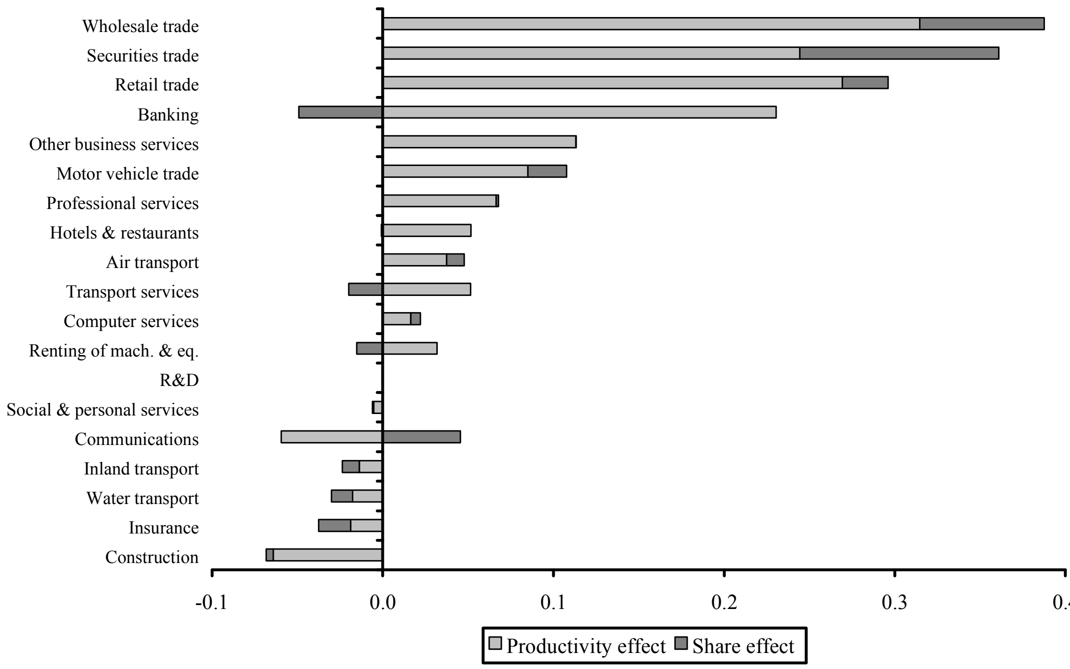
[106] This decomposition is very similar in spirit to the one presented in van Ark, Inklaar and McGuckin (2003a), except that the decomposition there was based on a shift-share decomposition of labour productivity growth.

(4.7) $\Delta \log y^{US} - \Delta \log y^{EU} = \sum_i prodty\_eff_i + \sum_i share\_eff_i + R^{US} - R^{EU}$.

By applying equation (4.7), the market services that have contributed most to the growth differential with the U.S. after 1995 can be identified and the cause of this difference can be traced to either faster productivity growth or a larger output share.[107]

To examine this issue, Figure 4.5 shows the difference in contribution of individual market services to labour productivity growth between the U.S. and Europe. It is immediately apparent that most of the difference in contribution can be traced to only a limited number of services industries, mostly industries involved in trade and finance. The chart also separates the overall difference into the productivity growth effect *(prodty_eff)* and the share effect *(share_eff)* from equation (4.7). This makes clear that most of the differences are due to faster productivity growth, although in securities trade and wholesale trade, the larger size of the industry in the U.S. also had a sizeable effect.

Figure 4.5 Difference in labour productivity contributions of market services, U.S. minus EU-15, 1995-2003



[107] Not much attention is devoted here to the reallocation term since it is quantitatively less important. However, it does provide an interesting insight into the impact of structural change in Europe and the U.S. Appendix 4.C shows some of the results.

Measurement issues

One issue that has not been dealt with in much detail so far are measurement problems. Adequately accounting for quality changes of manufactured products can be problematic, particularly for products undergoing rapid changes such as ICT (see e.g. Gordon (1990) and van Ark (2000)). In many service industries the main difficulty is to define a quantity concept that separates price changes from changes in output value. Triplett and Bosworth (2004) discuss the main measurement problems for many important services industries. Here the focus is on some of the questions that have been raised about the strong performance of the industries at the top of Figure 4.5.

In the securities trade industry, very rapid productivity growth rates in the U.S. have been questioned by, among others, Stiroh (2002b) because it is based on the volume of shares traded instead of the margins earned on these trades by the stockbrokers. Recently, statistical practices in this area have improved in the U.S.[108] McKinsey (2001) also shows that after refining and extending BEA output measures, labour productivity growth in this industry in the U.S. remains strong.

There has also been a debate whether rapid U.S. productivity growth in wholesale trade and retail trade reflects true productivity gains, or whether it is driven by measurement problems. The European Commission (2004) and Gordon (2004) stress that U.S. growth in the trade sector may be overstated. The main problem is that the volume of trade services is proxied by the volume of sales. For many goods, this assumption seems plausible: if twice as many cars are sold, car dealers will have delivered about twice as many services to customers. The assumption becomes more problematic if the volume of sales increases because of quality improvement of the goods, such as in the case of ICT goods. Although a Pentium computer represents much more computing power than a 286, the trade services needed to sell these computers are probably not much different.[109]

However, there is little concrete evidence on how important this issue is. Timmer and Inklaar (2005) show that real output growth in U.S. wholesale trade suffers from a noticeable upward bias. The bias in European wholesale trade is probably smaller, but not entirely absent either. The growth figures for retail trade are

[108] See McCahill and Moyer (2002).
[109] Most of these arguments can be found in Triplett and Bosworth (2004).

much less affected by such measurement problems, and the productivity growth gap in retail trade between Europe and the U.S. is not much reduced by measurement refinements. Although any adjustment to growth in wholesale trade would lower the contribution of this industry to aggregate growth, it would do little to detract from the overall importance of market services in explaining the U.S. productivity advantage.

4.4 Patterns of ICT use in the U.S. and Europe

ICT intensity measures

The next step of the analysis is to see whether there is a relationship between the strong performance of the industries in Figure 4.5 and the intensity of ICT use. To compare the intensity of ICT use across industries, it is necessary to have a good metric for ICT use such as the expenditure on ICT relative to the expenditure on other inputs. Other measures are, for example, the number of firms using the Internet for sales or purchases or the penetration of network technologies (OECD, 2002b, 2003). However, these measures are much harder to compare across industries or to the other input choices of a firm. However, since ICT is a general purpose technology, it seems more illuminating to focus on the ICT inputs than looking at specific uses.

Given the use of a production framework, the focus here is on investment-based measures. Specifically, let $P_t^i I_t^i$ stand for investment in current prices in asset *i* at time *t*. The simplest measure of ICT intensity is then $\sum_{ICT} P_i^i I_t^i \Big/ \sum_i P_i^i I_t^i$, or the share of ICT investment in total investment.[110] If investment series are available for a sufficiently long period of time, capital stocks can be calculated using the perpetual inventory method (PIM):

(4.8) $$K_t^i = (1-\delta^i)K_{t-1}^i + I_t,$$

where K_t^i is the capital stock at constant prices of asset *i* at time *t* and δ^i is the geometric depreciation rate of capital good *i*. The second measure of ICT intensity can then be calculated as the share of ICT capital in the capital stock at current prices, or $\sum_{ICT} P_i^i K_t^i \Big/ \sum_i P_i^i K_t^i$. In general, the ICT investment share will be larger than the ICT capital share because non-ICT assets such as structures have a much longer service life and hence, a lower depreciation rate (around 3-10%) than ICT assets (10-

[110] The group of ICT assets consists of computers, communication equipment and software.

30%). However, the capital stock share neglects the fact that ICT assets deliver more capital services because of a higher user cost. To take this into account, the ICT share in capital compensation is required. The ICT capital compensation share is defined as:

(4.9) $$\sum_{ICT} r_t^i P_i^i K_t^i \Big/ \sum_i r_t^i P_i^i K_t^i \; .$$

Similar to labour compensation, $\sum r_t^i P_i^i K_t^i$ gives the income that capital assets have to generate to cover their user cost. The gross real rate of return on a capital asset, $r^{i,}$ is calculated as:

(4.10) $$r_t^i = R_t + \delta_t^i - \dot{p}_t^i \, .$$

The gross return is determined by the internal rate of return R_t at time t, the depreciation rate of asset i and its rate of price change $\dot{p}_t^i$.[111] ICT assets demand a higher return than other assets because of a higher depreciation rate and rapid price declines. As a result, the ICT share of capital compensation will be higher than the ICT share of the capital stock.

We can also look at the share of ICT capital compensation in value added:

(4.11) $$\sum_{ICT} r_t^i P_t^i K_t^i \Big/ P_t^Y Y_t \; .$$

The main advantage of this last expression is that given cost minimization and constant returns to scale it is equal to the output elasticity of ICT for a general production function:[112]

(4.12) $$Y = f\left(L, K_{ICT}, K_{Non-ICT}\right).$$

Furthermore, equation (4.11) takes into account that some industries are more labour intensive than others as the productive impact of a given ICT share in capital compensation is likely to be smaller for a labour intensive than for a capital intensive industry. One problem with these intensity measures is that they are all input measures, while we are ultimately interested in the impact of ICT on output and productivity. Of course, as mentioned before, in a neo-classical framework, the output impact of ICT will be equal to the ICT share in value added as given in equation (4.11). However, this assumes away spillover effects from ICT reflected in TFP

[111] Usually a term reflecting corporate taxes and investment credits is also included in equation (4.10). However, as Erumban (2004) shows, taxes have only a limited effect on capital input growth, so these terms are omitted here. The internal rate of return is in this case taken as the return which equates total economy capital compensation with the observed capital stock at current prices.

[112] In general, the industry production function is specified in terms of gross output instead of value added and intermediate inputs are included amongst the inputs. Given separability of intermediate inputs, the equality of cost shares and output elasticities will hold.

growth. In reality, however, there is a lot of case-specific evidence of spillovers from ICT. One example is the retail-case as discussed by McGuckin et al. (2005) (see Section 4.5). Another example is from Olewiler (2002), who discusses how a relatively small ICT investment by the oil industry has fundamentally changed oil exploration methods. But although the impact of ICT may not be well captured by the intensity measures described here, the intensities should be useful as a first approximation.

To get some idea about the magnitude of the various ICT intensity measures, Table 4.2 shows the various measures discussed above for two broad sectors of the U.S. economy, production industries and market services, as well as the market economy as a whole in 1995. These estimates are based on a dataset containing investment and output data for 47 U.S. industries.[113] ICT investment consists of all investment in computers (IT hardware), communication equipment and software.

Table 4.2 ICT intensity measures for major U.S. sectors in 1995

	ICT investment share	*ICT capital stock share*	*ICT capital compensation share*	*ICT capital compensation in value added*
Production industries	15.3	3.2	11.8	4.7
Market services	33.3	13.0	32.1	8.5
Market economy	26.1	8.2	23.2	7.2
Rank correlation				
Investment share		0.97	0.97	0.81
Capital stock share			0.96	0.83
Capital compensation share				0.80

Sources: BEA, 1997 Capital Flow Table, extrapolated using BEA, Estimates of nonresidential fixed assets, detailed industry by detailed type, 1987-2003 (NAICS-based) and 1901-2001 (SIC-based). GGDC (2005) 60-Industry database (value added). Notes: Production industries includes agriculture, mining, manufacturing and utilities. Market services covers the other market industries. The (Spearman) rank correlation is calculated using data for 47 U.S. industries covering the market economy.

As the table shows, the services sector invests most strongly in ICT according to all intensity measures. Indeed, the services sector owns more than 85 percent of ICT assets in the U.S. economy.[114] The high ICT intensity of the services sector is not

[113] The basic source is the 1997 Capital Flow Table from the U.S. BEA (see Meade *et al.*, 2002) on the basis of which nearly all industries from the 60-industry database can be distinguished. The benchmark figures are extrapolated using detailed investment series by industry and asset from the BEA.
[114] As Inklaar, O'Mahony and Timmer (2005) show, this pattern is similar in Europe.

just due to the fact that services are less capital-intensive overall, since the ICT intensity is highest of the sectors even as a share of value added. The four intensity measures vary considerably in magnitude, but as the bottom panel of the table shows, the ranking of industries is very similar across measures. The average rank correlation between the four measures is 0.89. The rank correlation among the first three measures (investment, capital and capital compensation share) is even higher at about 0.97. Differences in capital intensity between industries explain why the ICT share in value added has a lower rank correlation with the other measures. Still, the various ICT intensity measures give a largely similar picture of which industries are intensive ICT users and which are less so. In the remainder, the ICT capital compensation share is used as the main measure of ICT intensity.

Can a distinct group of ICT users be identified?

In earlier work we have extensively focused on ways to distinguish between industries that are intensive users of ICT and industries that are less intensive users. Van Ark, Inklaar and McGuckin (2003a) looked at the share of ICT capital in total capital compensation to distinguish between intensive ICT-using and less-intensive ICT-using industries. An arbitrary cut-off point, namely the median, was used to distinguish ICT using industries from non-intensive users.

Of course, this typology can be criticized on grounds of the arbitrariness of the cut-off point between more intensive and less intensive ICT-use.[115] Indeed the literature on general purpose technologies suggests that the spectrum of ICT intensity will be much more gradual as technological opportunities only differ gradually across industries. Gradualism is confirmed in Figure 4.6, which ranks industries in the United States on the basis of the share of ICT capital compensation in total capital compensation in 1995. As the figure shows, most of the ICT producers and market services are on the left side of the chart whereas most of the production industries are on the right side.

An alternative approach to distinguish between intensive and less intensive ICT using industries is to look for a data-determined cut-off point using cluster analysis (see e.g. Peneder, 2003). One such approach to dividing observations into two (or more) groups is the *k-means* approach. Starting from an arbitrary grouping of

[115] See, for example, Daveri (2004).

industries, the absolute difference with the mean of each group is calculated. New groups are then formed by allocating industries to the group with the nearest mean. This process is repeated until no industries change between groups. This way, the intra-group variability is minimised.

Another clustering method is *hierarchical* cluster analysis. In this method, the distance (for example, the squared difference) between all observations is calculated. The two observations that are closest together are grouped into a cluster and the distance from this cluster to all other observations is calculated. This process is repeated until there is only one cluster left containing all observations. To get two groups of industries, one can simply go to the point in the hierarchy where all observations are part of either of two clusters. The distance from the cluster to all other observations can be calculated in a number of ways. Three commonly used methods are the average link, single link, and complete link methods. *Average link* uses the average ICT intensity of a cluster to calculate distances to all other observations. *Single link* uses the minimum distance from any cluster member to the other observations. *Complete link* uses the maximum distance.

Table 4.3 Number of U.S. industries classified in high ICT intensity cluster and correlation between ICT intensity measures

	ICT share in capital compensation			*ICT share in value added*		
	1987	1995	2003	1987	1995	2003
Number of industries in high intensity cluster						
K-means	14	9	15	10	7	8
Hierarchical						
Average link	8	9	8	2	4	3
Single link	2	9	1	1	4	1
Complete link	2	9	13	4	4	3
Rank correlation between ICT intensity measures						
	1987	1995	2003	1987	1995	2003
1987		0.83	0.78		0.72	0.64
1995			0.97			0.90

Notes: Average link uses the average ICT intensity of a cluster to calculate distances to all other observations. Single link uses the minimum distance from any cluster member to the other observations, complete link uses the maximum distance.

Figure 4.6 Share of ICT capital in total capital compensation in the United States for 1995

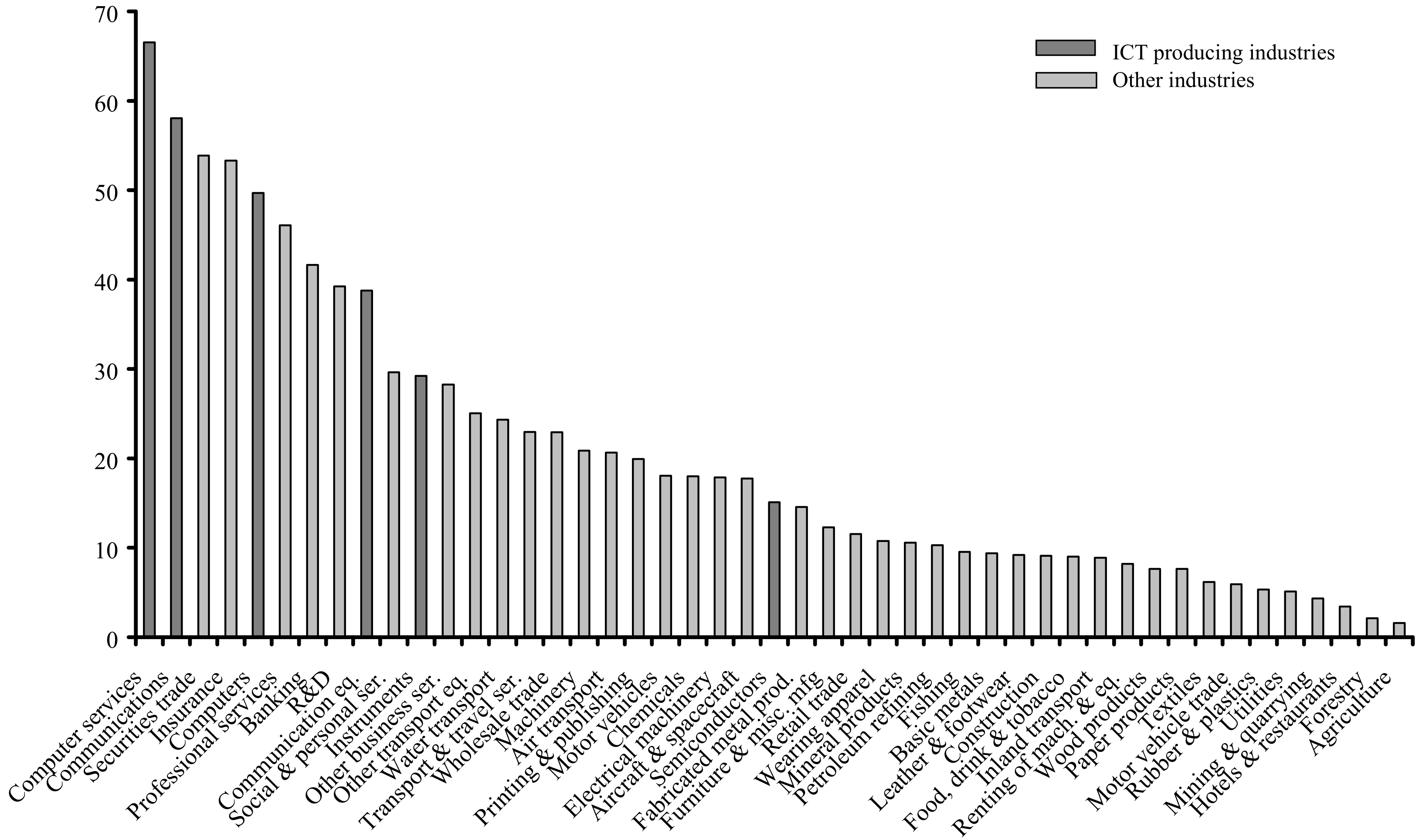


Table 4.3 shows the number of U.S. industries that is classified in the high ICT intensity cluster according to the different cluster analysis methods discussed above for various years.[116] For example, in 1995 the nine industries with the highest ICT share in capital compensation would be clustered into the ICT-using group of industries. Judging by these results, no clear group of ICT users can be identified. There are considerable differences between methods for a single year, between years and between ICT intensity measures. Using these results, one can either defend choosing only the most ICT intensive industry as ICT using or take the top 15 industries. The cluster analysis methods are also remarkably sensitive to small changes in the data: even though the correlation between the 1995 and 2003 shares of ICT in capital compensation is 0.97, the single link method places nine industries in the high intensity cluster in 1995, but only one in 2003. Overall this suggests that no clearly defined group of ICT users exists but instead that the change from highly ICT intensive to less intensive is gradual. Any analysis of the productive impact of ICT by industry should therefore be cautious in making a sharp distinction between ICT using and non-ICT industries.

4.5 Industry-level growth accounts and the contribution of ICT to growth

Growth accounts can provide information that is obscured when looking only at labour productivity growth by providing a framework in which the contribution to growth of different types of physical and human capital can be assessed and compared. However, data on investment by asset at the industry level is still scarce so the analysis is limited to five countries (France, Germany, Netherlands, United Kingdom and United States) and 25 market industries.[117] This section first gives an overview of the growth accounting methodology at the industry level and then moves on to a discussion of some of the data issues. The remainder of the section is devoted to a presentation of the results.

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[116] For the hierarchical cluster analysis, the squared difference between observations is used as a distance measure. Using the absolute difference does not change the results. For the cluster analysis, all 47 market industries have been used. The results are qualitatively similar if the ICT producing industries, which are mostly near the top of the ranking, are left out.

[117] In addition, there are an increasing number of country-specific studies with industry-level growth accounts and data on ICT investment. Some of these studies are for countries that are covered here (e.g. Oulton and Srinivasan (2005) for the UK, and van der Wiel (2001) for the Netherlands) and others are for other countries (e.g. Mas and Quesada (2005) for Spain).

Growth accounting at the industry level

Calculating capital stocks and rental prices

Capital input is measured by capital service flows, following the methodology pioneered by Jorgenson and Griliches (1967) and more recently implemented in Jorgenson, Ho and Stiroh (2005). Capital stocks are constructed using the perpetual inventory method (PIM) as in equation (4.8). The rental price for each asset is defined as the rate of return R at time t plus the depreciation rate minus the rate of inflation of the asset in question (see equation (4.10)). Growth in capital input is measured by capital service flows and is derived from the capital stocks by asset type as follows:

(4.13) $$\Delta \ln K_t = \sum_j \bar{v}_{j,t}^K \Delta \ln K_{j,t} \ ,$$

where $\bar{v}_{j,t}^K$ is the two-period average share of asset type j in total nominal capital compensation (implementing equation (4.9)). In the results below, the contribution of ICT capital services and non-ICT capital services are separately distinguished. ICT capital services are calculated by weighting each of the ICT capital stocks by the share of the asset in total ICT capital compensation. Non-ICT capital services are calculated analogously.

Aggregation and industry contributions

Section 4.1 provided an overview of the basic growth accounting methodology. Industry-level data adds the complication that results have to be aggregated to get industry contributions to aggregate growth. Jorgenson, *et al.* (2005) distinguish three methods to aggregate output and inputs across industries, namely the aggregate production function, the aggregate production possibility frontier and aggregation over industries. The third method is employed here because it is the most flexible. Specifically, the assumption that the prices of value added and inputs are equal across industries does not have to be made.[118] This means that industry growth rates of output and inputs are weighted by their share in aggregate value added to calculate contributions to aggregate labour productivity growth.

[118] An aggregate production function exists only if gross output prices, and hence value added prices, as well as input prices are equal across industries. For an aggregate production possibilities frontier, input prices need to be equal.

Combining the decomposition of aggregate labour productivity in (4.5) with equation (4.2), the decomposition of aggregate labour productivity growth into industry contributions can be written as:

$$(4.14) \qquad \Delta \ln y = \sum_i \overline{w}_i \left(\overline{v}_i^L \Delta \ln q_i^L + \overline{v}_i^{ICT} \Delta \ln k_i^{ICT} + \overline{v}_i^N \Delta \ln k_i^N + \Delta \ln A_i \right) + R .$$

In contrast to equation (4.2), equation (4.14) also includes a term reflecting labour quality, q_i^L. This term is calculated as the difference between the change in an index of labour input and growth of total hours worked. The labour input index is calculated in a similar fashion as capital services growth, but with different types of labour, distinguished by educational attainment.[119] Using this decomposition, the contribution of input and TFP growth from each industry to aggregate labour productivity growth can be calculated.[120] For example, the contribution of ICT-capital deepening in industry *i* to aggregate labour productivity growth is given by:

$$(4.15) \qquad ICTContr_i = \overline{w}_i \left(\overline{v}_i^{ICT} \Delta \ln k_i^{ICT} \right),$$

which is defined as the growth of ICT capital per hour worked in industry *i* weighted by the share of ICT capital compensation of industry *i* in aggregate nominal value added. The weight is the product of the share of industry *i* in aggregate value added ($\overline{w}_i$) and the share of ICT capital compensation in industry value added ($\overline{v}_i^{ICT}$). Similar calculations can be carried out for the contributions of non-ICT capital, labour quality and TFP. [121]

Growth accounting results

Table 4.4 shows the growth accounts for the total market economy as well as for the contributions from two industry groups, namely the (broad) ICT production sector and total market services from 1995 to 2003.[122] In addition to the four European countries, a column shows the (weighted) average results for these countries (referred to as EU-

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[119] See Inklaar, O'Mahony and Timmer (2005) for more details.

[120] Just as in Section 4.2, value added is used as the measure of output. As long as statistical offices use double deflation to estimate real value added from gross output and intermediate inputs, value added-based TFP is equal to gross output-based TFP divided by the value added to gross output ratio. See OECD (2001) for further discussion.

[121] For a more extensive description of methodology as well as the data sources, see Inklaar, O'Mahony and Timmer (2005). Estimates for recent years follow similar procedures. At this stage, no educational attainment data could be collected for years after 2000, so labour quality growth is assumed to be zero for those years.

[122] The "broad" ICT production sector includes electrical and optical equipment (ISIC 30-33) and telecommunications (64). Investment data is not available to distinguish computer services (72) in all countries.

4) which facilitates the comparisons with the macro-results presented in Section 4.2. The findings for the market economy are similar to those at the macro-level: labour productivity growth in the U.S. is higher than in Europe due to a combination of higher contributions from ICT capital deepening and TFP growth. The EU-U.S. gap in TFP growth from ICT production is somewhat smaller here than for the aggregate level (where the impact of ICT production was subtracted from aggregate growth on the basis of output shares) because the industry data also include telecommunications services, where Europe has a growth edge over the U.S.

Table 4.4 Sources of industry labour productivity growth, 1995-2003

	France	Germany	Netherlands	United Kingdom	EU-4	United States
Market Economy Labour Productivity Growth	***1.80***	***2.08***	***1.41***	***2.59***	***2.12***	***3.51***
of which:						
ICT capital deepening	0.46	0.54	0.81	0.77	0.63	1.27
Non-ICT capital deepening	0.32	0.37	0.71	0.71	0.54	0.60
Labour quality growth	0.21	0.05	0.12	0.23	0.14	0.11
Reallocation of hours	0.01	0.25	-0.35	-0.26	-0.08	-0.26
Total factor productivity growth	0.79	0.88	0.14	1.13	0.89	1.78
Contribution of ICT producing sector	*0.71*	*0.84*	*0.41*	*0.87*	*0.83*	*1.15*
of which:						
ICT capital deepening	0.03	0.06	0.08	0.14	0.09	0.23
Non-ICT capital deepening	0.02	0.07	0.11	0.05	0.05	0.08
Labour quality growth	0.02	0.01	0.03	0.02	0.03	0.01
Total factor productivity growth	0.64	0.69	0.19	0.65	0.67	0.83
Contribution of market services	*0.12*	*0.34*	*0.63*	*1.29*	*0.57*	*2.02*
of which:						
ICT capital deepening	0.33	0.38	0.60	0.53	0.44	0.84
Non-ICT capital deepening	0.00	0.13	0.25	0.40	0.20	0.27
Labour quality growth	0.15	0.02	0.07	0.15	0.07	0.07
Total factor productivity growth	-0.36	-0.19	-0.29	0.21	-0.14	0.85

The industry results bring out some of the earlier findings in sharper perspective. First, market services in both Europe and the U.S. account for between 75 and 80 percent of ICT capital deepening in the total market sector, with much smaller contributions from ICT producing industries. In terms of TFP contributions, however, the ICT producing sector is the most important source of TFP growth in Europe (0.67 percentage-points out of 0.89 percent growth). In the U.S., ICT production also makes a sizeable contribution, but market services are equally important. Indeed in the U.S., this sector generates 0.85 percentage points of growth, or half of market economy TFP growth. For the EU-4, the TFP contribution from market services is negative, -0.14 percentage points. The UK stands out among the four European countries for its relatively strong TFP performance in market services, although it still lags the U.S.

What is the evidence on TFP spillovers?

Table 4.4 suggests that the U.S. has managed to combine strong ICT investment in market services with high TFP growth. There is considerable firm-level evidence for the U.S. that ICT has a larger impact on productivity than suggested by its share in total cost, according to a survey of this literature by Brynjolfsson and Hitt (2000). A recent OECD (2004) collection of studies also shows that this result holds more widely than just for the U.S. In other recent work, Brynjolfsson and Hitt (2003) demonstrate that at the firm level, the benefits from ICT investment increase by a factor 5, up to seven years after the initial investment.

However, as the overview of literature in Stiroh (2002a) shows, the evidence at the industry-level or economy-wide is much less convincing. His finding for the total economy was confirmed in Section 4.2 and Stiroh's (2002a) own estimates show little or no evidence of spillovers from ICT capital accumulation to TFP growth at the industry level. Others, such as Basu, Fernald, Oulton and Srinivasan (2004) find more support, especially for the hypothesis that it takes time for firms to accumulate sufficient organizational capital to productively use ICT. O'Mahony and Vecchi (2005) also report findings that point towards spillovers.[123]

To more fully explore this issue for the industry data for Europe and the U.S., the following regression is estimated:

(4.16) $$\Delta \ln A_{it} = \alpha + \beta\left(\bar{v}_{it}^{ICT} \Delta \ln K_{it}^{ICT}\right) + \varepsilon_{it} .$$

Using equation (4.16), the productive impact of ICT capital can be evaluated. Specifically, if β is not significantly different from zero, ICT capital makes a "normal" contribution to growth, given by its cost share and the entire productive impact of ICT is accounted for in the calculation of TFP growth. This equation is similar to one of the equations estimated in the more extensive study of Stiroh (2002a) for U.S. manufacturing.[124]

Equation (4.16) is estimated using ordinary least squares (OLS). The standard errors of the parameters have been corrected for autocorrelation and heteroscedasticity

[123] In general, see Stiroh (2003) for a survey of studies estimating the output elasticity of ICT capital.

[124] Stiroh also simultaneously estimates the impact of the other inputs on TFP, but these are omitted here to facilitate the focus on ICT capital.

using the procedure of Newey and West (1987). The estimates in Table 4.5 are shown with only a single constant term as well as with fixed effects, with a dummy included for each country/industry pair. The regressions with only a single constant show whether higher ICT contributions are related to higher TFP growth. The fixed effects models establish whether a rise in the contribution from ICT capital, in a particular industry in a specific country, is related to higher TFP growth. These fixed effects models may be relevant if certain unmeasured industry- and country-specific factors are important. For example, it could be the case that the regulatory environment of an industry in a country influences TFP growth, but not ICT investment. Eliminating this unobserved heterogeneity through a fixed effects model may be important to identify the impact of ICT on TFP growth (see e.g. Griliches and Mairesse, 1998).[125]

Table 4.5 The impact of ICT on TFP growth, annual growth rates for 1979-2003 in Europe and the U.S.

TFP=a+b*ICT+e	*All countries*	*France*	*Germany*	*Netherlands*	*UK*	*U.S.*
Single constant	-1.01*	-0.99	-1.43	-1.25*	-0.78	-0.96*
	(0.27)	(0.90)	(0.81)	(0.48)	(0.66)	(0.42)
Fixed effects	-1.47*	-1.98	-3.14*	-1.49	-0.71	-1.11
	(0.45)	(1.39)	(1.50)	(0.89)	(0.50)	(0.69)

Notes: * denotes significantly different from zero at 5% level. Heteroscedasticity and autocorrelation-consistent standard errors are shown in parentheses. Dependent variable is industry TFP growth between 1979 and 2001. Independent variable is the contribution of ICT capital to output growth. In the fixed effects estimates, a dummy is introduced for each country/industry pair. Estimates for all market industries and all countries include 2875 observations (23 years, 25 industries, 5 countries), the other columns include 575 observations.

Table 4.5 shows the estimates of equation (4.16) for all market industries. When pooling across countries, a higher (or rising) ICT contribution actually leads to lower TFP growth. Most of the country estimates are insignificantly different from zero or negative too.[126] Overall, these results are in line with those reported in Stiroh (2002a), who also reports a number of significantly negative estimates of ICT on TFP growth, although he manages to trace these to the ICT producing industries.

One reason why no positive relationship between ICT and TFP is found in the industry data may be that the effect of ICT on TFP occurs only with a lag, for example, because complementary investments in organizational change must be made

[125] Experiments with demand-side instruments to take further endogeneity problems into account, show comparable results.

[126] Removing the ICT producing manufacturing industry from the sample does not change the qualitative results. Estimates for only services industries are also not noticeably different. The fixed effects estimates are mostly larger, in absolute sense, than the single constant estimates. The reason for this is not immediately clear since this result also shows up for individual countries. However, in a statistical sense the two sets of estimates do not differ, so the issue is of limited importance.

first. Basu *et al.* (2004) build a theoretical model and present some results that suggest this may be important. In their empirical exercise, they explain TFP growth in each industry, averaged over 1995 to 2000, by the ICT contribution to growth for 1980-1990, 1990-1995 and 1995-2000. For the U.S. they find a negative effect of ICT for 1995-2000 on TFP and positive effects for the first two periods. This suggests that lags may be important. The analysis of Basu *et al.* (2004) however, is strictly cross-sectional and the choice of periods and lags is somewhat arbitrary.

Brynjolfsson and Hitt (2003) test a similar hypothesis of possible time lags using firm-level data, arguing that the best way to pick up the effects of earlier ICT investment on current TFP is by taking longer differences of the data. so instead of 1-year growth rates, they look at growth rates over 2, 3 and more years. Their main finding is that the ICT impact on TFP growth rises as longer differences are taken, with the 7-year difference showing an impact of ICT that is 5 times as large as the 1-year difference.

Other methods have also been used to distinguish short-run and long run effects of ICT use. O'Mahony and Vecchi (2005) apply the pooled mean group (PMG) estimator of Pesaran *et al.* (1999) to estimate the output contribution of ICT capital.[127] With this methodology, O'Mahony and Vecchi (2005) find a long-run effect of ICT on output that is higher than is expected on the basis of cost shares. This implies evidence of spillovers from ICT use. While their result is useful and interesting, the link to firm-level studies such as Brynjolfsson and Hitt (2003) is somewhat lost. The first goal here is to use similar methods as Brynjolfsson and Hitt (2003) to see whether the firm-level results hold up at the more aggregate industry level. A secondary goal is to gauge the robustness of the Basu *et al.* (2004) results to different lag lengths and periods.

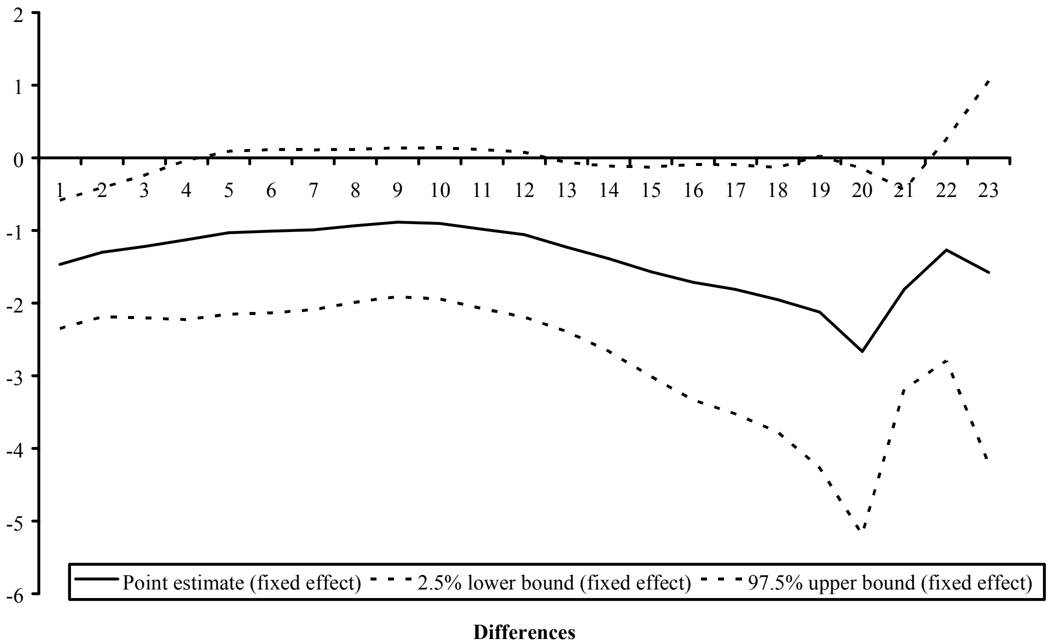
It is not immediately clear which method (using long differences or including lagged ICT investment) best captures the idea of a long-run effect of ICT on TFP. A priori, the lagged specification would seem to capture the idea of complementary investments better. If a firm starts an ICT investment project at time t, it might be that for example the largest TFP benefits accrue at time $t+5$. However, by that time a new ICT investment project (perhaps in a different part of the organization) may have

[127] The PMG estimator allows short-run dynamics to differ across industries and countries, but constrains the long-run effect to be the same.

commenced. Also, summing TFP contributions over the years would include the years in which the peak TFP impact was not yet reached as well. However, it is straightforward to test both methods. Furthermore, they both have the added advantage that measurement errors become less prominent, since these errors are unlikely to be highly correlated across years.

As a first step, ever longer differences are calculated following the same procedure as Brynjolfsson and Hitt (2003). When increasing the difference length, their approach is to use overlapping periods. So for three-year differences, they first calculate the difference from year 1 to year 4, next from year 2 to year 5, etc. This procedure does build in a certain amount of autocorrelation, since any measurement error in for example year 3 is included in the first, second and third observation. The Newey-West procedure should correct for this, however, and the results are qualitatively similar if no overlapping periods are used. Figure 4.7 shows the parameter as well as confidence bands for fixed effects estimates, ranging from 1-year to 23-year differences.[128]

Figure 4.7 Effect of ICT on TFP growth in the EU-4 and U.S. at the industry level, 1-year to 23-year difference



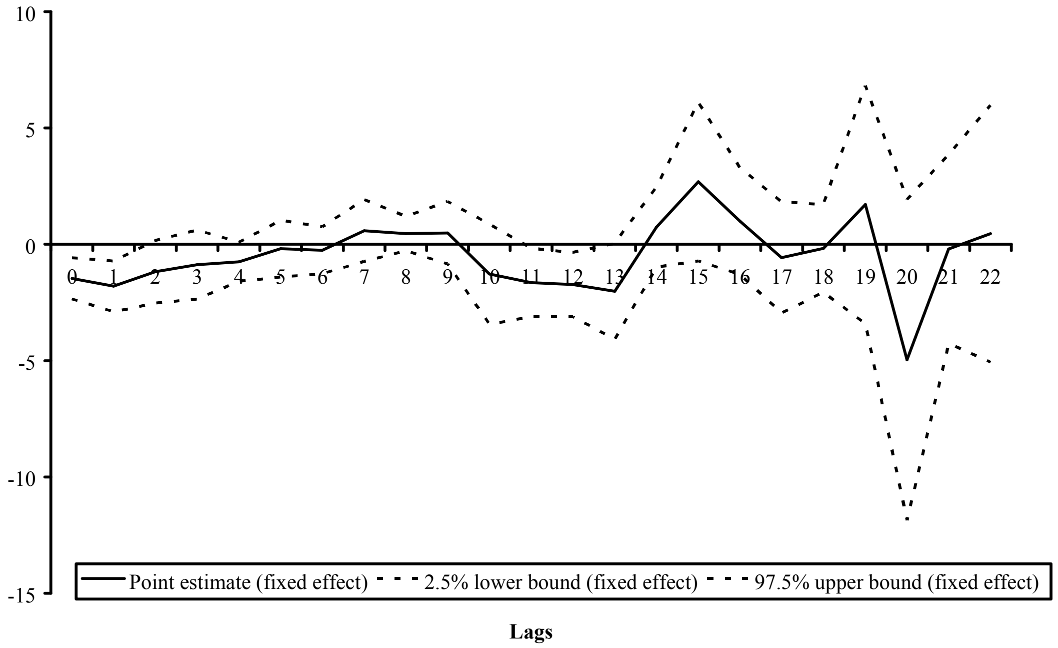
The estimate for 1-year differences is the same as shown for OLS with fixed effects from Table 4.5. This estimate is significantly negative at the 5% level. From 5-

[128] To estimate fixed effects, at least two observations per industry are needed, so a 23-year difference is the maximum possible.

year differences to 12-year differences, the coefficient is insignificantly different from zero and after the 12th year, the upper bound fluctuates around zero.[129] Hence, Figure 4.6 suggests that a rising ICT contribution in an industry does not have a significant impact on TFP growth over differences longer than four years and a negative effect for the first four years. In any case, a strong positive relationship is certainly not supported by these data.[130]

The other possibility that needs to be explored is whether the ICT contribution in one year has an impact on TFP growth in the next year or years after that. For this exercise, only one-year differences are used, although experiments with combinations of lags and longer differences suggest a similar story as increasing lags in combination with one-year differences. Figure 4.8 shows the estimated impact of ICT on TFP growth, from the contemporaneous effect up to a 22 year lag. As before, fixed effects estimates are presented.

Figure 4.8 Effect of ICT on TFP growth in the EU-4 and U.S. at the industry level, contemporaneous effect to 22-year lag



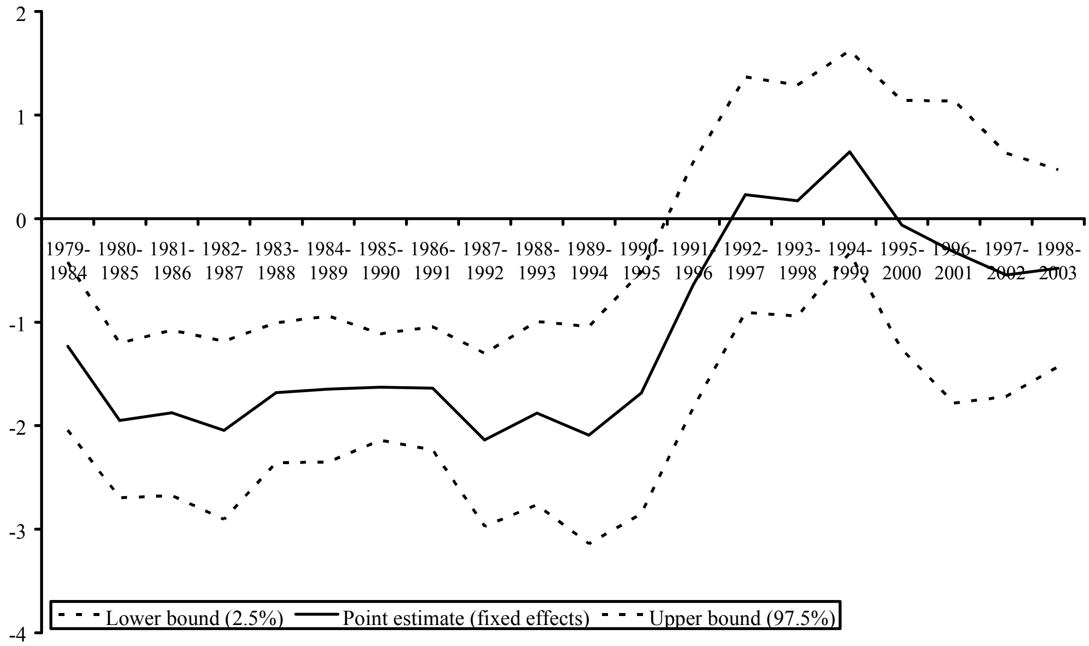
The contemporaneous effect and at the effect of a one-year lag are significantly negative but from two years onwards, the estimated effect is not significantly different

[129] If only a single constant is used, the coefficient remains significantly negative, even for very long differences. This is mainly the result of tighter confidence intervals and not so much lower point estimates. As the fixed effects model removes certain unobserved heterogeneity, it seems preferable.
[130] The individual country results are not shown, since no country shows consistently positive or negative effects.

from zero. Estimates with a single constant are significantly below zero up to a lag of five years, and insignificant afterwards, which can again mostly be traced to tighter confidence intervals. As before, the country-specific results do not diverge noticeably from the overall pattern of Figure 4.8.

So far, only the full sample of observations for all years has been analyzed. One might argue, however, that the relationship between ICT and TFP growth has changed over time. To investigate this possibility, equation (4.16) is also estimated for each 5-year period in the sample.[131] Figure 4.9 shows the regression coefficient for 1979-1984, then the 1980-1985 coefficient up to the 1998-2003 coefficient. Throughout the 1980s, the ICT effect remains significantly negative, but starting with the 1991-1996 period, the coefficient becomes indistinguishable from zero. So during the 1990s, ICT capital generated productivity effects in line with the cost of ICT capital, suggesting normal returns.

Figure 4.9 The relation between ICT contributions and TFP growth for subsequent sets of 5-year differences, 1979-1984 to 1998-2003



[131] Five-year differences were chosen since Figure 4.6 shows that on average over the full period, the ICT effect is not significantly different from zero. Using differences of other lengths does not alter the qualitative results. Including a single constant instead of fixed effects also does not affect the pattern. If similar rolling estimates are made using lags instead of long differences, the coefficients fluctuate more from period to period, but the pattern of significantly negative in the 1980s to indistinguishably different from zero in the 1990s is unchanged.

The analysis so far suggests that the significantly negative results, shown in Table 4.5, paint a picture that is too pessimistic about ICT's impact on TFP growth. Taking longer differences or allowing for lags between the ICT investment and the impact on TFP, mostly eliminates the significant negative results, although the point estimates remain predominantly negative. These results seem to cast some doubt on the estimates shown by Basu *et al.* (2004), who find a significant positive impact of the 1990-1995 U.S. ICT contribution on 1995-2000 TFP growth. In the setting of this study, they find a positive impact of the 5-year lagged ICT contribution with (roughly) 5-year differences. Although their specification is not separately reported, the more comprehensive set of specifications that were tested here shed some doubt on the robustness of their findings. Figure 4.9 shows that some of the point estimates for the 1990s are positive, but never significantly so.

It might also be argued that the U.S. and UK are ahead of the Continental European countries, as suggested by Table 4.4. Figure 4.10 therefore takes the use of sub samples one step further by carrying out the 5-year regressions separately for the three continental European countries (France, Germany and Netherlands) and the two Anglo-Saxon countries (UK and U.S.) in the dataset.

Figure 4.10 The relation between ICT contributions and TFP growth for subsequent sets of 5-year differences, Continental Europe vs. Anglo-Saxon countries

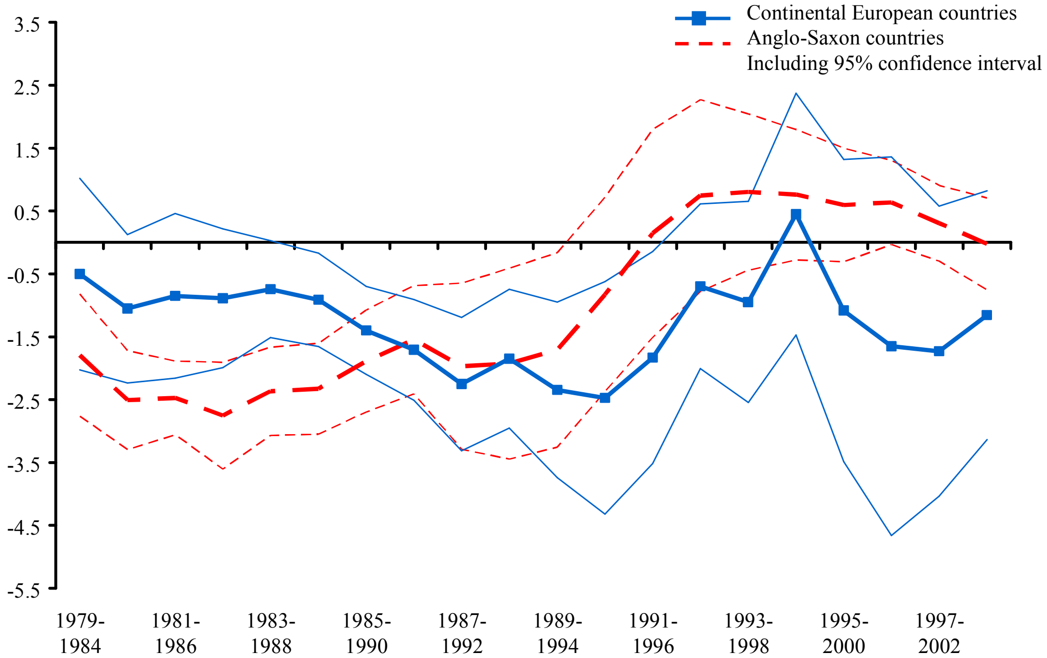


Figure 4.10 shows that the effect of ICT on TFP growth is U-shaped for the Continental European countries: ICT capital has no significant impact on TFP growth up to the mid-1980s, a significantly negative effect up to the 1991-1996 period and from the 1991-1996 period onwards there is again no significant effect. There is some suggestion that a similar U-curve might exist for the Anglo-Saxon countries, but as it is located a couple of years earlier, the left tail of the U-shape cannot be directly observed because of lack of data. It should be stressed once again, however, that ICT has at best no effect on TFP growth in both the Continental European and Anglo-Saxon countries. The main change from the 1980s is that ICT is no longer a drag on TFP growth in the 1990s.

Some complementary evidence for the U-curve hypothesis can be found in Morrison (1997), who shows that high tech capital in U.S. manufacturing earned its marginal cost from the early 1970s until about 1980 and again from around 1990 onwards. During the 1980s though, the marginal returns from ICT fell short of the marginal cost. In other words, it seems likely that the U-curve exists in all countries in our sample. This pattern may be indicative of relatively straightforward, direct, 'hard' savings from ICT investment that can be realized quickly. However, before further savings can be realized, new organizational forms need to be developed and experimented with. In addition a strong competitive process is needed to weed out failing experiments with investment in organizational innovations.

Compared to the many firm-level studies on the impact of ICT capital on productivity, the results presented here are still puzzling. Brynjolfsson and Hitt (2003) estimate a number of long differences models and find a normal return to computer investment already at one-year differences, while at longer differences the return becomes five times as high. The results here show that even with very long differences, only a normal return can be observed at the industry level. Furthermore Brynjolfsson and Hitt (1996) find that after accounting for fixed firm effects, the impact of ICT on growth decreases. They take this as evidence of important firm-specific effects, possibly related to the strength and flexibility of the organization. The industry estimates here show little difference in point estimates, which can be taken as evidence that these firm effects are mostly a within-industry phenomenon. In other words, industries may have strong performers, but at the industry-level this averages out. Brynjolfsson and Hitt (2000) also point out that within-industry variation in ICT investment and productivity can lead to a lower correlation between these measures at the industry level due to the averaging out process described above.

4.6 Concluding remarks

This chapter has provided some new perspectives on the relationship between ICT and productivity growth from an international comparative perspective. First of all, estimates up to 2004 show that the EU-U.S. growth gap, which opened up around 1995, grew even larger after 2000. The gap can mostly be attributed to the sharp acceleration of total factor productivity growth in the U.S., which appears to be located mainly in market service industries. European growth has declined further, and in particular, market services have performed quite poorly in recent years. This evidence gives support to the hypothesis that the European Union is presently not on a track to realize the same productivity gains from ICT as the U.S.

Further analysis focused on the possibility that there is a difference in timing of the productivity effects of ICT between Europe and the U.S. The argument would then go that many European countries are still in a transition process towards a new phase of productivity gains from ICT usage, which the United States have already realized. To this end the direct relationship between ICT use and TFP growth at the industry level has been estimated, to identify any productivity spillover effects of ICT use. The results suggest that, at the industry level, ICT does not earn super-normal returns, even when taking longer differences or lags into account. The analysis did establish a pattern suggesting that ICT earned its normal returns in the early phase of ICT investment (1970s, early 1980s), followed by a period of negative effects from ICT on productivity (late 1980s) with a return to normal returns after several years. This U-shaped pattern of returns on ICT shows up clearly for the three continental European countries (France, Germany and the Netherlands), and there is also evidence for a similar pattern in the UK and the U.S. several years earlier.

These results might be better understood when relating them to the literature on general purpose technologies and, more specifically, to the idea that the pervasiveness of technologies, such as ICT, involves a significant amount of time before its productivity effects are exploited (see, for example, Bresnahan and Trajtenberg, 1995). One might speculate that the early normal returns on ICT are the result of the direct productivity effects of ICT production and ICT investment (called "hard savings" here). The "negative spillover"-period may be related to a phase of investments in human capital and knowledge capital as well as organizational innovations which do not immediately result into an acceleration of productivity growth. It takes time before the combination of ICT investment and intangible investments and innovations (here called the "soft savings"), have an effect on productivity. This interpretation of the results is also in line with the firm-level evidence which emphasizes the importance of human capital and organizational innovations (Brynjolfsson and Hitt, 2000, 2003; OECD, 2004).

The idea that ICT can generate 'hard' and 'soft' savings with an impact that is phased over time is consistent with detailed studies of individual industries. For example, McGuckin, Spiegelman and van Ark (2005) show that in retail trade, ICT investment had an immediate impact on productivity growth through hard savings. For example, the introduction of barcode scanning allowed for more efficient check-out systems without much further investment. However, the same barcode technology has enabled a reorganization of the supply chain and the introduction of new shopping concepts. These soft savings not only require heavy investment in ICT, but also investments in new complementary technologies (RFID, transportation technology) and organizational changes (new shopping concepts, supplying shops more often).

These findings also have methodological implications. The econometric analysis of the ICT impact provided new insights compared to the growth accounts, especially by showing a U-curve of the productive impact of ICT investment. However, the growth accounting framework did provide a consistent framework that defines the normal returns from ICT investment. Furthermore, the output elasticity of the other capital inputs and labour did not need to be estimated, but could be assumed equal to their cost share.

This leaves open the question why firm-level studies find positive spillovers whereas the industry estimates show neutral effects. A plausible explanation is that within an industry, some leading firms invest heavily in ICT and organizational change and reap the accompanying productivity gains. But there are also laggards with lower productivity growth. These laggards may have also invested heavily in ICT, but were less successful in realizing soft savings. Although in time these laggards are likely to either exit or catch-up due to competitive pressures, this inevitably takes time. In the meantime, industry performance will reflect both leading and lagging firm performance. To find out whether this explanation holds in practice, further firm-level research into these aggregation effects is needed.

The most relevant issue for policy is why Continental European countries are slower in realizing the effects from soft savings than the UK and the U.S. One possible line of argumentation is that the process of realizing soft savings involves much trial-and-error. It therefore requires an entrepreneurial environment and competitive labour and product markets that allow efficient firms to grow and weed out inefficient ICT users. There is substantial evidence from industry level studies on regulation (e.g., Nicoletti and Scarpetta, 2003) as well from firm-level studies on the dynamics of firm performance (e.g, Bartelsman, *et al.*, 2005) that confirm the need for a conducive regulatory environment to generate productivity growth. Many of the continental European institutions, in particular in the area of labour and product markets, inhibit the reallocation of resources to the most productive companies. The European economic environment creates too little room for good firms to excel and for failing firms to exit the market so as to free up resources for the much-needed transition. This may particularly affect investments in firm-specific resources, such as human and organizational capital, which unlike ICT are not easily transferred on markets and may stay for too long in firms that are not productive. This direct link between regulation and soft savings is an important area for further research.

Appendix 4.A ICT-production TFP

Section 4.2 presented estimates of ICT-production TFP. Similar estimates were also presented in Timmer *et al.* (2003), but a number of changes were made to the methodology. The main idea is to 'back-out' TFP growth that can be traced to ICT producing industries and is different from the 'bottom-up' industry approach from Section 4.5. The starting point is TFP growth of ICT producing industries in the United States. These growth rates are assumed to be equal across countries because there are few countries that account for quality changes as thoroughly as the U.S. Although a growing number of countries now use constant-quality (hedonic) prices for computers, few do so for telecommunications and semiconductor manufacturing.

The definition of ICT-production is limited here to the manufacturing of computers (ISIC 30), semiconductors (321) and telecommunications equipment (322). This definition is narrower than those used in Sections 4.3 and 4.5. Section 4.3 closely follows the OECD (2002) classification and also includes insulated wire and cable (ISIC 313), part of the instruments industry (331), telecommunication services (64) and computer services (72). The definition in Section 4.5 is coarser due to the limits of the capital data and covers the entire electrical and optical equipment industry (ISIC30-33) and telecommunications (64). The reason for choosing a more narrow definition is that U.S. TFP growth rates in those three industries are most likely to be applicable to other countries. For example, Inklaar *et al.* (2005) report large differences in TFP growth rates in telecommunications between the four European countries and the U.S. and similarly, there are considerable differences in labour productivity growth between countries in insulated wire and cable and instruments.

U.S. labour productivity growth in computers, semiconductors and telecom equipment is available from the GGDC (2005) 60-industry database. Capital deepening estimates are based on the 1997 Capital Flow Table, which provides investment by asset data for each of the three industries. Investment trends are only available at a more aggregate level. Next, TFP growth is changed from a value added-basis to gross output basis by multiplying by the value added to gross output ratio. This way, cross-country differences in the value added to gross output ratio can be taken into account.

Domar weights are used to estimate the contribution of ICT production to TFP growth in both the U.S. and the European countries. These weights are defined as industry gross output divided by aggregate value added and were originally suggested by Domar (1961). When summed across all industries, the weights will generally exceed one to account for the fact that TFP growth in any industry will also have effects on downstream industries through cheaper intermediate inputs. For the European countries, value added for each of the ICT industries is taken from the 60-industry database. Input-output tables, mostly from Eurostat, give data on value added to gross output ratios for a number of years in the late 1990s. For earlier and later years, these ratios are assumed to have remained constant. Multiplying value added and the value added to gross output ratios gives estimates of gross output for the ICT producing industries and this is used to calculate Domar weights.

Appendix 4.B Estimating TFP levels

In the literature on growth convergence, controlling for initial levels of GDP per capita or per hour worked is common practice (see e.g. Baumol, 1986). In these cases, only the relative price (PPP) of GDP is needed to make income or labour productivity comparable across countries. However, to estimate TFP levels, a correction also has to be made for differences in capital levels. Once those are available, TFP levels can be calculated in analogous fashion to TFP growth rates:

$$\log\left(\frac{A^X}{A^U}\right) = \log\left(\frac{Y^X}{Y^U}\right) - \bar{v}^L \log\left(\frac{L^X}{L^U}\right) - \left(1 - \bar{v}^L\right)\log\left(\frac{K^X}{K^U}\right). \tag{4.B1}$$

In equation (4.B1), superscripts X and U denote the countries. Analogous to growth accounting, the relative TFP level can be calculated as the relative GDP level minus the weighted relative labour input level and relative capital input level (Caves, Christensen and Diewert, 1982).

GDP levels in U.S. dollars are available from the GGDC/TCB Total Economy Database (2005). Relative labour input is from the same source and calculated as the ratio of total hours worked. For comparisons of capital input across countries, we need an estimate of the rental price in one country relative to another, the so-called capital service PPP (PPP^K):

$$PPP^K_{k,m,j} = \frac{r_{k,j}}{r_{m,j}} = \frac{\left(R_{k,t} + \delta_j - \dot{p}_{k,j,t}\right)}{\left(R_{m,t} + \delta_j - \dot{p}_{m,j,t}\right)} PPP^I_{k.m,j}\,. \tag{4.B2}$$

Equation (4.B2) gives an expression for the rental price of asset j in countries k and m, using the same variables as in equation (4.10) (since the same depreciation rate are used across countries, no country subscript is attached). Most elements of equation (4.B2) are readily available, since these are inputs for the calculation of the gross rate of return. The only missing element is the investment PPP (PPP^I). Expenditure PPPs for 35 assets for 1999 from the OECD (2002a) are used here. The investment PPPs for the 35 assets are aggregated to investment PPPs for each of the six assets in this study using a multilateral (EKS) aggregation procedure. The resulting capital service PPPs are used to convert capital compensation to U.S. dollars. Summing over the assets gives total capital input in U.S. dollars for each country.

Appendix 4.C The reallocation effect

Although the reallocation effect is quantitatively less important for labour productivity growth than growth within industries, it provides useful insight into the impact of structural change. Recall from equation (4.5) that the reallocation effect is defined as follows:

(4.C1) $$R = \sum_i \overline{w}_i \Delta \ln H_i - \Delta \ln \sum_i H_i \ .$$

There is no exact decomposition of this expression into industry contributions, but the following approximation comes very close:[132]

(4.C2) $$R \approx \sum_i \overline{w}_i \Delta \ln H_i - \sum_i \overline{s}_i \Delta \ln H_i = \sum_i (\overline{w}_i - \overline{s}_i) \Delta \ln H_i \ .$$

In equation (4.C2), $\overline{s}_i$ denotes the two-period average employment share, $H_i / \sum H_i$. In other words, the contribution of an industry to the aggregate reallocation of hours is determined by its growth in total hours worked and the difference between the industry output share and employment share. This difference is large when the industry labour productivity level is higher than the aggregate productivity level.

[132] The approximation is due to the substitution effect, whereby the employment shares of each industry change over time. The squared difference between the exact measure and the approximation is roughly 1000 times smaller than the standard deviation of the exact measure over time.

Figure 4.C1 Contributions by industry groups to market economy reallocation of hours, EU-15 and U.S., 1987-2003

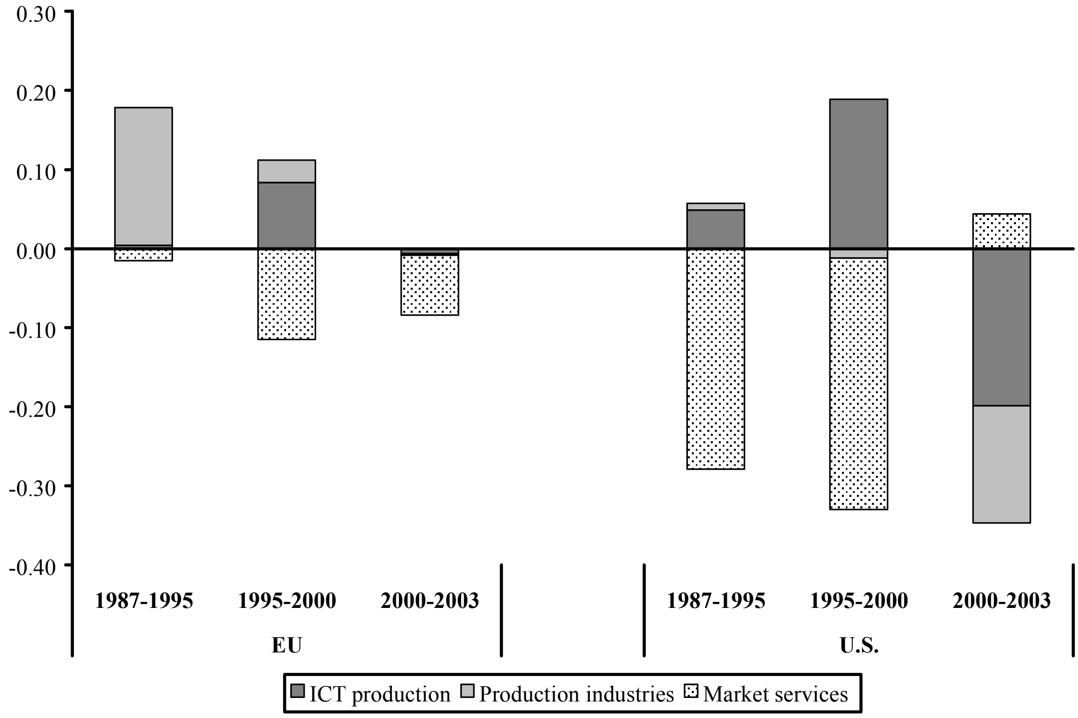


Figure 4.C1 shows the (approximate) industry contributions to the market economy reallocation effects by industry group. A first observation is that the size of the reallocation effects is larger in the U.S. than in the EU-15. The industry pattern is also different. In Europe, the production sector contributed positively to aggregate reallocation, and hence to labour productivity growth, while in the U.S., the main effects from this industry group are negative. Also interesting is that after 2000, market services contributed positively in the U.S., while in earlier periods the contribution was negative. In Europe, the contribution from market services was negative throughout the period.

First of all, these results suggest that the degree of structural change is much higher in the U.S. than in Europe. Indeed, when averaging the absolute reallocation contributions over the full period, U.S. reallocation is more than 40 percent higher than EU-15 reallocation. This does not seem implausible, judging by for example the lower degree of employment protection in the U.S. (Nicoletti, *et al.*, 2000). But to establish this, we would need to know whether this difference is due to larger employment changes at the industry level or possibly due to a greater dispersion in labour productivity levels. Although a similar decomposition as in the main text is possible, the resulting effects are hard to interpret.[133]

It makes more sense to find direct measures of productivity level dispersion and gross employment change. A measure for productivity level dispersion is the standard deviation of productivity levels relative to the aggregate. To avoid overstating the importance of small sectors, industries are weighted by their employment share. Gross employment change is measured here as the absolute growth of total hours worked, again weighted using industry employment shares.[134] Table 4.C1 shows these two summary measures for the EU-15 and U.S. There is no large difference in the dispersion of productivity levels, but the difference in gross employment change is substantial. This suggests that the difference in the size of the reallocation effects can be traced to larger employment flows.

Table 4.C1 Summary measures of productivity level dispersion and gross employment change, EU-15 and U.S., 1987-2003

	1987-1995	1995-2000	2000-2003
Labour productivity dispersion			
EU-15	0.32	0.36	0.38
U.S.	0.32	0.37	0.41
Gross employment change			
EU-15	2.46	2.20	1.51
U.S.	3.04	3.08	2.56

Note: Labour productivity dispersion is defined as the standard deviation of labour productivity levels relative to the aggregate, weighted by employment share. Gross employment change is defined as the absolute growth in total hours worked, weighted by employment share.

This leaves the different industry pattern of the reallocations to be explained. As discussed above, the most notable differences can be seen between 2000 and 2003. However, given that the post-2000 period includes a recession in the U.S. and slow growth in Europe too, this finding should not be overstated. The negative contribution from market services for most of the period can, to an important extent, be traced to non-professional business services in both Europe and the U.S. In the U.S., this can be

[133] See also van Ark, *et al.* (2003a).
[134] At the industry level, only the net change in employment is available, so this measure understates true gross job flows.

further traced to strong employment growth of employment agencies.[135] After 2000, U.S. employment in this industry declined by about 5 percent per year. However, as persons employed by employment agencies work in other parts of the economy, it is hard to give an economic interpretation to developments after 2000. The most that can be said is that a notable part of the reallocation term is probably due to an increased importance of employment agencies to increase labour input flexibility.

[135] In Europe, this information is usually not available, although for the Netherlands, similar observations can be made.

Chapter 5 Cyclical productivity[136]

5.1 Introduction

In the short run, output and productivity tend to move together in many countries and across a wide range of industries.[137] In recent years this observation has gained increased prominence, as each proposed explanation for the observed procyclicality of productivity has important implications for modelling the business cycle and measuring technical change. The goal of this chapter is to evaluate the role of increasing returns to scale and unmeasured input utilization in explaining procyclical productivity growth. This is motivated by the success of the model by Basu and Fernald (2001), who find that these two factors can fully account for cyclical productivity of the aggregate U.S. economy. The analysis also serves as a test for the assumptions of constant returns to scale and well-measured inputs inherent in the growth accounting results presented in the previous chapter.

Although there is a large and growing empirical literature looking at returns to scale and input utilization, the exercise in this chapter is the first to directly test whether the Basu-Fernald (2001) model is similarly successful in reducing output-productivity correlations outside the U.S. and to what extent the model applies not only at the aggregate but also at the industry level. I confirm the main finding of Basu and Fernald (2001) for the aggregate U.S. economy, but also show that the Basu-Fernald model does not eliminate procyclicality in many industries. Even after correcting for possible non-constant returns to scale and unmeasured input utilization, around one quarter of U.S. industries still show significant procyclical productivity growth.

For European countries, the evidence on the Basu-Fernald model is more mixed, with some success at the aggregate level while it again falls short at the industry level. One possible reason for these findings is that the analysis relies on a proxy for unmeasured input utilization, hours worked per person. If the change in

[136] This chapter is largely based on Inklaar (2005). See the acknowledgements for further details.
[137] This effect is distinct from the Verdoorn effect, where larger cumulative output leads to higher productivity through learning-by-doing.

average hours worked is not a good indicator of changes in unmeasured inputs, the explanatory power of the model will fall short. The original arguments for this proxy were largely based on work practices in U.S. manufacturing and this may not be very relevant in Europe and in services industries.

Even though the Basu-Fernald model is far from perfect, it does provide a good opportunity to evaluate the impact of adjustments for variable returns to scale and unmeasured input utilization on measured productivity growth. The main result is that although the estimated growth rates change, the adjustments are not large enough to affect the main stylized facts as presented in the previous chapter. For example, the lead of the U.S. in market services TFP growth after 1995 remains unchanged. This suggests that the standard growth accounting assumptions do not give a misleading picture of productivity growth.

The final finding of this chapter is of a more technical nature, but nevertheless important for the analysis. Identification of the production functions estimated in this literature tends to rely on relatively weak demand-side instruments. Following Shea (1993) and Baily, Bartelsman and Haltiwanger (2001), I construct a set of industry-specific instruments capturing downstream intermediate demand. A recently developed statistical test confirms that these instruments are less prone to weak-instrument bias than the more commonly used instruments such as the real oil price. Therefore, using these downstream indicators allows for a greater degree of confidence in the estimates presented here than in some of the earlier studies in this literature.

The remainder of this chapter is organized as follows. First, the main stylised facts of cyclical productivity are introduced alongside the most important proposed explanations for this phenomenon from the literature. The next section presents the theoretical framework for the analysis. Section 5.4 discusses the estimation framework and the data used. The results are shown in Section 5.5, first with regards to the production function estimates. The next part focuses on the cyclicality of the technical change residual while the final part of the section discusses the sensitivity of the standard TFP growth measure. Section 5.6 summarizes and discusses some of the implications of the results.

5.2 Background

One of the more robust stylised facts in the macroeconomic literature is that output and productivity move together in the short run. Table 5.1 illustrates this phenomenon by showing the correlation between output growth and total factor productivity (TFP) growth in European countries and the United States. With few exceptions, the correlations are positive and highly significant. Although other filtering methods exist, we focus on these correlations mainly because Basu and Fernald (2001) do so.

Table 5.1 Correlation between annual total factor productivity and GDP growth, Europe and the U.S., 1979-2003

Austria	0.62*	Italy	0.54*
Belgium	0.64*	Luxembourg	0.78*
Denmark	0.47*	Netherlands	0.48*
Finland	0.78*	Portugal	0.61*
France	0.7*	Spain	-0.42*
Germany	0.92*	Sweden	0.61*
Greece	0.82*	UK	0.55*
Ireland	0.78*	US	0.75*

Notes: * denotes a correlation significantly different from zero at the 5% level
Source: GGDC Total Economy Growth Accounting Database (2005a)

Three explanations for cyclical productivity are popular in the literature: 1) procyclical technology shocks, 2) increasing returns to scale and 3) unmeasured input utilization.[138] The first explanation is the most obvious: if technology shows transitory, high-frequency fluctuations, it should not come as a surprise that output will show similar fluctuations and hence, productivity will be procyclical. This argues in favour of models where technology drives the business cycle as in Real Business Cycle Theory (e.g. Cooley and Prescott, 1995). Under increasing returns to scale, a decline in inputs in a recession will lead to a more than proportionate decline in output and hence lower output per unit of input. If these increasing returns are related to imperfect competition, changes in government expenditure can directly lead to procyclical productivity.[139] Increasing returns can also be due to external effects,

[138] See Basu and Fernald (2001) for a more extensive overview of these explanations. They also include reallocation of resources across sectors as an explanation at the aggregate level. As the focus of this chapter is mostly on the limits of their model at the industry level, it is not discussed any further here.
[139] Increases in government expenditure increases (future) taxes and thereby reduce labour income and hence, labour supply. However, increases in government expenditure also increase output and thereby labour supply. Under imperfect competition the former effect dominates the latter, leading to a larger

implying that output in an industry can affect output in other industries and these effects need to be modelled.[140] If the third explanation holds, firms adjust not only measured inputs such as capital and labour, but also unmeasured inputs like the utilization rate of capital or the labour effort per hour worked. Therefore, during a growth slowdown or a recession the decline in productive inputs will be understated and observed productivity will be procyclical. Differences in the importance of these explanations can also shed important light on the effect of the institutional structure across countries. For example, as Vecchi (2000) shows, Japanese firms hoard more labour than American firms due to lower transaction costs in Japan, which affects the dynamics of the economies in question.

Different explanations for cyclical productivity also have implications for the interpretation of productivity growth as technical change. Researchers such as Gordon (1993, 2000) try to separate the 'cyclical' from the 'structural' part of productivity growth. This approach might be useful to isolate a measure of technical change if unmeasured input utilization were the leading cause for procyclical productivity growth. However, as Basu and Fernald (2001) argue, if increasing returns to scale and reallocations are important, cyclical productivity is a 'structural' phenomenon since it reflects the ability of firms to produce output given a certain level of inputs. As a result, a more formal analysis is needed to identify technical change.

There is an extensive literature that tries to distinguish between the various explanations of procyclical productivity.[141] Most of these papers focus on the U.S., but there is international evidence as well, most notably from Caballero and Lyons (1990), Oliveira Martins, Scarpetta and Pilat (1996) and Vecchi (2000) which so far

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effect of government expenditure increases on output than on employment; see the survey by Rotemberg and Woodford (1995).

[140] The literature on short-run externalities is rather unclear about the exact nature of these spillovers. Long-run externalities are generally related to knowledge spillovers, but to explain short-run externalities, the authors at most refer to the idea that 'thick markets' are responsible. In other words, more activity in one market 'spills over' to other markets. See Bartelsman, Caballero and Lyons (1994) for a discussion.

[141] See amongst others: Hall (1988, 1990), Roeger (1995), Oliveira Martins, Scarpetta and Pilat (1996), Basu and Fernald (1997) and Diewert and Fox (2004) on returns to scale and markups. Markups and returns to scale are comparable as economic profits are generally modest. See Caballero and Lyons (1990, 1992), Bartelsman, Caballero and Lyons (1994), Sbordone (1997) and Vecchi (2000) on externalities. See e.g. Berndt and Fuss (1986), Basu and Kimball (1997), Burnside, Eichenbaum and Rebelo (1995), Burnside (1996), Hart and Malley (1996), Vecchi (2000), Basu and Fernald (2001) and Basu, Fernald and Shapiro (2001) on labour hoarding and correcting for unmeasured input utilization. Finally, Basu and Fernald (2001) and Basu, Fernald and Shapiro (2001) stress the importance of reallocations between sectors.

is confined to production function and related estimates. In a recent study for the U.S., Basu and Fernald (2001) use production function estimates to evaluate whether these reduce the correlation between output and the technology residual they estimate. On the basis of this exercise Basu and Fernald (2001) conclude that there is only a limited role for increasing returns to scale outside durable manufacturing and that unmeasured input utilization and reallocations explain the cyclicality of aggregate U.S. productivity. In this chapter the same approach is used to analyze whether their conclusions also apply to individual industries and other countries. First, I discuss the production model that underlies the empirical analysis.

5.3 A model of cyclical productivity

This section discusses a model that is commonly used to study the cyclicality of productivity growth.[142] A firm produces according to the following production function:

(5.1) $$Y = F(zK, eHN, M, A).$$

Output, denoted by *Y*, is produced using capital *K*, workers *N*, average hours worked *H* and intermediate inputs *M*, given the state of production technology *A*.[143] Additional choice variables for the firm are the intensity of capital use *z* and the effective labour effort *e*. In a model with costless input adjustment, the latter two variables are irrelevant. However, when we assume that labour and capital are quasi-fixed inputs, firms can adjust to shocks in the short run only by varying average hours worked, labour effort and the intensity of capital use. Following Basu and Fernald (2001), we think of *z* as being determined by the number of work shifts. Higher intensity of capital use is costly due to a shift premium.[144]

The firm can pay its workers more in order to ensure higher effort levels, given the number of hours worked per worker. If pay is raised immediately, labour compensation could be used as an indicator of labour utilization. However, if the extra compensation is by way of better promotion chances or when it is spread out

[142] Similar types of models are presented in many of the referenced papers. A model that leads to the same estimating equation is given in Basu and Fernald (2001).

[143] In this concept, gross output is the output concept instead of value added as in Chapter 4. The reason is that while this choice is not crucial for analyzing TFP growth, it does affect the econometric analysis that follows.

[144] Another theoretical mechanism commonly used is to assume that if capital is used more intensively, machinery wears out more quickly and depreciation is higher (see e.g. Imbs, 2003). However, the shift premium fits more closely with the utilization proxy used here. See Basu and Kimball (1997) for a model that explicitly combines both mechanisms.

over several years, it will not fully show up in the labour compensation figures of a single year. The level of effort can be interpreted directly as the intensity of work, but an employee might also divide his time between productive work and training or other learning activities. In the latter case, the firm might respond to a positive demand shock by shifting workers from non-productive to productive work without having to pay a higher wage immediately. This will be costly because future labour productivity improvements will be lower as less human capital will have been accumulated.[145]

If the firm minimizes costs and is a price taker on the market for factor inputs, inputs will be purchased up to the point where the marginal product equals factor prices. This means we can construct an input growth index (see e.g. Basu and Fernald, 1997):

(5.2) $$dX = s_L(de + dH + dN) + s_K(dz + dK) + s_M dM\ ,$$

where *d(.)* is an operator giving the percentage growth of the variable and s_x is the two-year average share input x in total cost.[146] Note that equation (5.2) gives the Törnquist approximation to the continuous-time Divisia index of input growth. This way, very few restrictions are placed on the underlying production function.

The standard calculation of total factor productivity growth as the Solow residual subtracts the growth of inputs from the growth of output. This will only give a valid measure of technical change under constant returns to scale. In general, if we assume neutral technical change, the relationship is as follows:

(5.3) $$dY = \gamma dX + dA\ ,$$

where γ denotes the returns to scale. The problem with estimating equation (5.3) is that neither effort levels nor the intensity of capital use is easily observable so that one only measures a biased version of equation (5.2):

(5.4) $$dX^* = s_L(dH + dN) + s_K dK + s_M dM = dX - s_L de - s_K dz\ .$$

The usual solution to this problem is to find a proxy for input utilization. For the manufacturing sector, a number of researchers have used capacity utilization measures (i.e. Shapiro, 1996). Other studies have proposed energy use or materials use as a proxy for capital utilization (e.g. Burnside *et al.*, 1996). However, such measures do not reflect changes in labour utilization and are often not available

[145] See Hart and Malley (1996) for arguments along these lines.
[146] An alternative would be to use constant shares over the full period, but this has only a small impact on the results discussed in Section 5.4.

outside manufacturing. Abbott, Griliches and Hausman (1998) propose to use changes in average hours worked as a proxy for both labour and capital utilization. This was formalised in the model of Basu and Kimball (1997). Their rationale for this proxy is that if optimising firms adjust inputs along one margin, namely average hours worked, they will also adjust along unobserved margins. As long as labour effort increases with the rise in average hours worked, growth of the latter variable will be a valid proxy for labour utilization. Similarly, if the only way to increase capital utilization in the short run is to increase the number of shifts and hence, average hours worked, the growth in average hours worked will also be a good proxy for capital utilization. Equation (5.3) can then be written entirely in terms of observable variables:[147]

(5.5) $$dY = \gamma dX^{*} + \gamma\xi dH + dA \,.$$

In this equation, ξ. is the effect of changes in the utilization proxy on output growth. Although data on average hours worked are available for all sectors of the economy, the interpretation of this variable as a proxy for unmeasured input utilization seems to be most relevant for manufacturing industries. Most non-manufacturing industries do not work in shifts and many workers are not paid by the hour, leading to less reliable measures of hours worked.

Another proxy, which is also available economy-wide, is intermediate inputs use. The rationale for using this proxy, as originally advanced by Basu (1996), is that if capital and labour utilization goes up, this is partly reflected in higher use of intermediates such as energy or raw materials. Intermediate inputs make up on average nearly half of all input cost, so one would expect parameter γ to adequately pick up any utilization effects as well. Adding changes in intermediate inputs per hour worked as done by Vecchi (2000) may be problematic since intermediate inputs are then included as part of input growth and as a separate explanatory variable.[148]

No explicit role is given to external effects in equation (5.5), although some researchers such as Caballero and Lyons (1990, 1992) and Vecchi (2000) argue their importance. There are two reasons for this. First, adding aggregate output growth to

[147] Basu, *et al.* (2001) use the cyclical part of average hours worked instead of the growth in average hours worked. In practice, they estimate this cyclical part using a Hodrick-Prescott filter with a very high smoothing parameter, removing an almost linear trend (see Chapter 3), so only the mean growth of average hours worked is removed, with no impact on parameter estimates.
[148] The next section also discusses an adjustment to equation (5.5) to take this problem into account for growth in average hours worked.

equation (5.5) may indeed pick up the effect of growth in other industries. However, as Sbordone (1997) argues, is may just as well be a proxy for demand-induced utilization changes. Second, while it is interesting to know whether increasing returns to scale are internal or external to the firm or industry, in the present analysis the main focus is on whether returns to scale can explain procyclical productivity growth. Equation (5.5) gives the general estimation framework to analyse the cyclicality of productivity growth.[149] A number of econometric issues need to be dealt with first, however.

5.4 Methods and data

Econometric methodology

We estimate two specifications, one including only the returns to scale parameter γ, and another specification which includes both returns to scale and the correction for unmeasured input utilization in the form of parameter ξ:

(5.6a) $$dY_{i,j,t} = \mu_{i,j} + \gamma_j^1 dX_{i,j,t}^* + \varepsilon_{i,j,t}^1,$$

(5.6b) $$dY_{i,j,t} = \mu_{i,j} + \gamma_j^2 dX_{i,j,t}^* + \xi_j dH_{i,j,t} + \varepsilon_{i,j,t}^2.$$

Output growth of industry *i* in country *j* at time *t* is the dependent variable in both regressions. In (5.6a), measured input growth is the only explanatory variable while in (5.6b) the growth in average hours worked is included to proxy for unmeasured input utilization changes. Input growth is a weighted average of the growth in labour, capital and intermediate inputs (equation (5.4)). In both specifications a country/industry fixed effect, $\mu_{i,j}$, is included as well. One of the goals of this work is to see to what extent European countries show different results from the U.S., so the parameters are allowed to vary by country. Productivity growth is partly accounted for through the fixed effect and it partly ends up in the residuals $\varepsilon_{i,j}$. The results from Basu and Fernald (2001) suggest that (5.6a) should give returns to scale estimates significantly greater than 1, while (5.6b) should give significantly positive estimates of ξ. Note that in equation (5.5), parameter ξ was interacted with

[149] Basu, *et al.* (2001) also give considerable attention to including adjustment costs in their output and input measures, which are calibrated using the estimates of Shapiro (1986). While in theory, this approach has merit, Hall (2004) finds relatively strong evidence against adjustment costs for capital or labour using U.S. industry data. Outside the U.S., the evidence is even scarcer so such adjustments are omitted.

γ. In practice taking this nonlinearity into account has little effect on the results as γ is close to one.

One of the objectives of this chapter is to provide comparable estimates to Basu and Fernald (2001). However, in specification (5.6b), growth in average hours worked is included both as part of input growth and as a separate explanatory variable. This is likely to bias the elasticity estimates, so a modified version of (5.6b) is also estimated where input growth, dX^*, is calculated excluding the growth in average hours worked.

An important problem with estimating equations (5.6a) and (5.6b) is that optimising firms set their levels of inputs and outputs simultaneously in response to productivity shocks. Therefore we need variables unrelated to industry productivity shocks but relevant for input growth to identify γ and ξ. Most of the literature has relied on relatively weak instruments, such as the world price of oil (Hall, 1988), to estimate variants of equations (5.6a) and (5.6b). Some have even relied on OLS estimates to avoid small-sample bias in IV estimates (e.g. Diewert and Fox, 2004). To lessen the weak instrument problem, downstream indicators of industry demand are used here.

Shea (1993) proposed to use input-output tables to identify industries with close demand links but relatively modest reverse links. If one takes, for example, the metal industry and the car industry, higher output in the latter industry will likely induce higher demand in the former industry. As a result, growth in the car industry is a relevant indicator for output in the metal industry, which satisfies the first requirement for a good instrument. In this case, however, it is not clear whether output changes in the car industry are sufficiently exogenous to productivity shocks in the metal industry because a notable part of intermediate inputs of the car industry come from the metal industry. Baily, Bartelsman and Haltiwanger (2001) constructed a weighted average of growth in downstream industries using all industries that buy output from a certain industry and for which these purchases represent less than five percent of intermediate inputs. In constructing the downstream instruments here, the same procedure was followed.

Data

A quite extensive dataset is needed to estimate the model described in Section 5.3. For the most part, the same industry growth accounting database is used as in the previous chapter, but there are some differences. First, to estimate full production functions, data on gross output and intermediate inputs are collected, in addition to the value added, capital and labour data from Chapter 4. Since the UK does not apply double deflation procedures in most of their value added estimates, no gross output series can be constructed that is consistent with value added, at least at constant prices. The UK is therefore omitted from the analysis in this chapter. A further change is in the calculation of the gross return on capital assets:

$$r_t^i = R_t^E + \delta_t^i - \dot{P}_t^i . \quad (5.7)$$

Instead of an internal rate of return (*R*), an external rate is used here, which is assumed equal to the government bond yield (from the IMF's *International Financial Statistics*). This adaptation was made in order to avoid assuming constant returns to scale in one part of the analysis and estimating those same returns later on.

Finally, information is collected on gross output at current and constant prices from the National Accounts of the various countries. Especially for the 1980s, prices for gross output are frequently not given in the National Accounts. In those cases either producer price indexes are used or price indexes are estimated based on implicit value added deflators. Intermediate inputs at constant prices are implicitly estimated based on gross output and value added at constant prices.

To construct the downstream indicator for each country, information is needed on deliveries by industry *x* to industry *y*. Benchmark input-output tables are used for each of the countries.[150] Although the sales shares of industries are likely to change over time, experiments using annual input-output tables for the Netherlands show that the impact on the indicators is limited. Therefore, only a single input-output table is used for 1995 (France and the Netherlands), 1997 (United States) and 2000 (Germany). The downstream indicators are calculated at the industry detail of the GGDC 60-industry database and then aggregated to the level of the 25 market industries covered here.

5.5 Results

First of all, it is useful at this point to compare how the various instrument sets perform when confronted with the data. As shown by Stock and Yogo (2004), the F-statistic from the first-stage regression where the endogenous variable is explained by

[150]To be precise, both industry-by-industry and product-by-industry (use) tables are used. Industry-by-industry tables are conceptually to be preferred, but in practice differences will be modest.

the instruments, is a useful statistic to test for instrument weakness.[151] The first column of Table 5.2 shows the average F-statistic across industries based on the first-stage regressions that aim to explain (measured) input growth by the current value and one lag of the downstream indicator for each industry in each country. The second column shows the same results from regressions with the so-called 'Hall-Ramey' instruments as explanatory variables.[152] As the table shows, in each country the downstream indicators generate a considerably better fit than the more widely used Hall-Ramey instruments.[153] As the last two columns show, in many of the 25 industries used here, the simultaneity bias inherent in OLS estimation can be reduced by 90 percent or more by using the downstream indicators, while the Hall-Ramey instruments lead to estimates that are much more biased towards the OLS estimates.[154] Based on these results, we may confidently rely on the downstream indicators to estimate equations (5.6a) and (5.6b).

Table 5.2 Comparing the fit of first-stage regressions explaining input growth, downstream indicator vs. Hall-Ramey instruments

	Average first-stage F-statistic		*Number of industries with IV bias less than 10% of OLS bias*	
	Downstream indicator	Hall-Ramey	Downstream indicator	Hall-Ramey
France	15.8	6.7	13	3
Germany	11.9	3.5	12	1
Netherlands	14.6	4.7	12	1
U.S.	13.2	5.7	8	2

First and third column: Regression with the growth of inputs as dependent variable and the current value and one lag of the downstream indicator as independent variables. Second and fourth column: Regression ith the growth of inputs as dependent variable and the current value and one lag of oil price change and growth of real government spending as independent variables. Third and fourth column: Number of industries where the first-stage F-statistic exceeds the critical value of 9.08 (third column) and 10.83 (fourth column), using Table 1 of Stock and Yogo (2004).

[151] To be precise, this is the F-test of joint significance of the explanatory variables, or the explained sum of squares over the residual sum of squares, corrected for degrees of freedom.
[152] These instruments are the current value and one lag of the change in the oil price relative to the GDP deflator and the growth of real government spending. The political party of the president is excluded, as it has no straightforward counterpart in other countries and is usually the weakest instrument of the three (e.g. Hall, 1988). Similarly, military expenditure is broadened to all government spending for easier cross-country comparability.
[153] F-statistics for individual industries in each country are shown in Appendix Table A2.
[154] As Basu and Fernald (1997, p. 258) note, the first stage F-statistic of equation (6a) using the Hall-Ramey instruments is around three using their data, which is comparable to the results in Table 5.2.

Production function estimates

In this section, the estimation results from equations (5.6a) and (5.6b) are presented. In all cases, two-stage least squares is used to estimate the parameters with the current value and one lag of the industry-specific downstream indicators as instruments. To improve efficiency, first-stage coefficients are allowed to vary by industry.[155] The standard errors of the parameters have been corrected for autocorrelation and heteroscedasticity using the procedure of Newey and West (1987).

As discussed in the previous section, three specifications are considered, namely equation (5.6a), equation (5.6b) with growth of average hours worked included in the aggregate input measure and equation (5.6b) with growth in average hours worked excluded from the aggregate inputs. Table 5.3 shows the estimates of returns to scale based on the first specification. Estimates that are significantly different from one (constant returns to scale) are marked by an asterisk.[156] The results are shown for groups of industries, as the time series dimension (23 observations) is too short for reliable inference at the industry level.[157] Indeed, for individual industries some very large, very small and even negative returns to scale are found (see Appendix Table 5.A3). As Table 5.3 shows, there is evidence of increasing returns to scale in each of the countries, with significant returns in particular for the market economy as a whole and in durable manufacturing. Excluding agriculture and mining tends to increase the parameter estimates. The largest effect of this can be seen in French non-manufacturing, where decreasing returns to scale are found. When looking only at the services sector (by excluding agriculture and mining), returns to scale are insignificantly different from one.

[155] In principle, it is also efficiency-enhancing to explicitly take into account any cross-sectional dependence of the residuals in a three-stage least squares procedure. However, since the number of industries is larger than the number of years, the estimated covariance matrix is not of full rank. Pesaran (2004) suggests an alternative procedure if the errors have a factor structure, which involves adding the cross-industry (weighted) averages of the dependent and independent variables to the regression. However, in an economic sense, this would be a specification that attempts to test for external effects as in Caballero and Lyons (1990, 1992). To avoid such complications, simple two-stage least squares is used.

[156] Appendix Table 5.A4 shows the same results, but using Hall-Ramey instruments instead of downstream indicators. There only durable manufacturing shows significant increasing returns.

[157] The period between 1979 and 2003 is 24 years, but one year is omitted because a lagged value of the downstream indicator is used as an instrument.

Table 5.3 Estimates of returns to scale to inputs, unadjusted for unmeasured input utilization, for France, Germany, Netherlands and U.S., 1979-2003

	France	Germany	Netherlands	U.S.
Market economy	0.98	1.12*	1.01	1.13*
	(0.06)	(0.04)	(0.07)	(0.04)
Market economy excluding agriculture & mining	1.06	1.15*	1.08*	1.12*
	(0.06)	(0.04)	(0.04)	(0.04)
Durable manufacturing	1.10*	1.08	1.04	1.16*
	(0.03)	(0.05)	(0.05)	(0.05)
Non-durable manufacturing	0.81	1.10	1.04	0.93
	(0.13)	(0.05)	(0.04)	(0.07)
Non-manufacturing	0.76*	1.04	0.97	0.98
	(0.10)	(0.07)	(0.06)	(0.05)
Services	0.88	1.04	1.06	1.01
	(0.09)	(0.08)	(0.06)	(0.04)

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs as independent variable. Estimation is done for a panel of industries, with industry fixed effects included (not shown) using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Parameters in the first stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and autocorrelation, are shown in parentheses. * denotes parameters significantly different from one at the 5% level. See Table 5.A3 for definitions of industry groupings.

In earlier work, Basu *et al.* (2001) have shown that adding changes in average hours worked as a proxy for unmeasured input utilization reduces the estimates of returns to scale. Table 5.4 shows the results for the same specification. In most cases, the estimates of returns to scale have decreased compared to Table 5.3, although especially in France and Germany, the differences are relatively small. Indeed, for these two countries, the same industry groups show returns to scale estimates that are significantly different from one. However, in the Netherlands and the U.S., estimates have gone down to such an extent that the constant returns to scale hypothesis is not rejected for any industry group. Still, the U.S. is the only country where the utilization parameter is positive and significant, while the other countries show many negative and sometimes even significantly negative parameter estimates.

Table 5.4 Returns to scale of inputs with a correction for unmeasured input utilization, 1979-2003

	Returns to scale			
	France	Germany	Netherlands	U.S.
Market economy	0.98	1.12*	0.97	1.04
	(0.06)	(0.04)	(0.07)	(0.06)
Market economy excluding agriculture & mining	1.06	1.15*	1.05	1.03
	(0.05)	(0.04)	(0.04)	(0.06)
Durable manufacturing	1.12*	1.07	1.02	1.12
	(0.03)	(0.04)	(0.04)	(0.07)
Non-durable manufacturing	0.80	1.10	1.01	0.87
	(0.13)	(0.05)	(0.05)	(0.08)
Non-manufacturing	0.76*	1.03	0.96	0.95
	(0.09)	(0.06)	(0.06)	(0.07)
Services	0.87	1.10	1.08	1.02
	(0.09)	(0.07)	(0.06)	(0.05)
	Utilization correction			
Market economy	-0.40	0.03	-0.34*	0.64*
	(0.34)	(0.23)	(0.14)	(0.23)
Market economy excluding agriculture & mining	-0.81	-0.10	-0.29*	0.63*
	(0.45)	(0.23)	(0.11)	(0.23)
Durable manufacturing	-0.37*	0.17	-0.26*	0.29
	(0.11)	(0.18)	(0.08)	(0.26)
Non-durable manufacturing	0.06	-0.08	-0.13	0.45*
	(0.15)	(0.14)	(0.07)	(0.22)
Non-manufacturing	-0.01	-0.40*	0.08	0.30
	(0.25)	(0.20)	(0.14)	(0.27)
Services	-0.51*	-0.93*	-0.29*	-0.07
	(0.19)	(0.29)	(0.09)	(0.18)

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs and growth of average hours worked as independent variable. Parameters are estimated for a panel of industries, with industry fixed effects included (not shown). Parameters are estimated using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Parameters in the first stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and auto correlation, are shown in parentheses. * denotes parameters significantly different from one (returns to scale) or zero (utilization correction) at the 5% level. See Table 5.A3 for definitions of industry groupings.

The U.S. results are different from those of Basu *et al.* (2001) who find strongly significantly positive parameters for each of the industry groupings from Table 5.4. For comparison, Appendix Table 5.A5 shows the same estimation results as Table 5.4, using Hall-Ramey instruments as Basu *et al.* (2001) instead of using downstream indicators. As the utilization effect is not uniformly significant in this specification either, it suggests that differences between the Basu *et al.* (2001) results and the results presented in Table 5.4 are due to the use of a different dataset.[158] Specifically, their dataset, which is based on the work of Jorgenson and Stiroh (2000), contains more industries (33 vs. 25) and more years (31 vs. 23). As a result their estimates are

[158] In addition, some persistently decreasing returns to scale are also apparent, which demonstrates some of the problems with weak instruments.

likely to be more precise.[159] Furthermore, even though the utilization proxy performs badly in all industry groups, the negative estimates for services suggest that growth in average hours worked is even less suitable in services than in manufacturing. The Jorgenson-Stiroh dataset only includes eight non-manufacturing industries and three of these cover utilities and construction, where work practices are probably more comparable with manufacturing industries than with, say, finance or business services. This difference in composition of the dataset might therefore also be important.

Table 5.5 Returns to scale of inputs with a correction for unmeasured input utilization, excluding average hours worked from aggregate inputs, 1979-2003

	Returns to scale			
	France	Germany	Netherlands	U.S.
Market economy	0.97	1.13*	0.99	1.05
	(0.06)	(0.04)	(0.07)	(0.06)
Market economy excluding agriculture & mining	1.06	1.16*	1.07	1.04
	(0.05)	(0.04)	(0.04)	(0.06)
Durable manufacturing	1.12*	1.07	1.04	1.12
	(0.03)	(0.04)	(0.04)	(0.07)
Non-durable manufacturing	0.80	1.10	1.04	0.88
	(0.13)	(0.05)	(0.05)	(0.08)
Non-manufacturing	0.76*	1.03	1.01	0.97
	(0.09)	(0.06)	(0.06)	(0.07)
Services	0.87	1.09	1.09	1.02
	(0.09)	(0.07)	(0.06)	(0.04)
	Utilization correction			
Market economy	-0.09	0.41	-0.12	0.92*
	(0.35)	(0.23)	(0.14)	(0.22)
Market economy excluding agriculture & mining	-0.48	0.27	-0.02	0.90*
	(0.46)	(0.23)	(0.10)	(0.22)
Durable manufacturing	-0.06	0.50*	-0.00	0.64*
	(0.11)	(0.18)	(0.08)	(0.25)
Non-durable manufacturing	0.25	0.19	0.02	0.62*
	(0.14)	(0.14)	(0.07)	(0.22)
Non-manufacturing	0.25	-0.03	0.36*	0.61*
	(0.25)	(0.18)	(0.12)	(0.25)
Services	-0.19	-0.49	0.14	0.31
	(0.21)	(0.29)	(0.09)	(0.17)

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs and growth of average hours worked as independent variable. The growth of inputs is modified to exclude growth in average hours worked. Parameters are estimated for a panel of industries, with industry fixed effects included (not shown). Parameters are estimated using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Parameters in the first stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and auto correlation, are shown in parentheses. * denotes parameters significantly different from one (returns to scale) or zero (utilization correction) at the 5% level. See Table 5.A3 for definitions of industry groupings.

[159] Another reason is probably that Basu *et al.* (2001) could use system estimation methods to increase efficiency; see footnote 155.

As discussed in Section 5.3, including growth in average hours worked both in aggregate inputs and as a separate explanatory variable may bias the estimate of ξ. Table 5.5 therefore shows estimation results based on equation (5.6b), but without the growth of average hours worked being included in aggregate inputs.[160] Compared to Table 5.4, the utilization proxy in the U.S. is now also significantly positive in non-manufacturing. Furthermore the estimates of scale returns are almost unchanged, but the significantly negative utilization effects from Table 5.4 have now disappeared. However, except in the case of durable manufacturing in Germany and non-manufacturing in the Netherlands, the estimates on the utilization correction are not significantly positive either. These results suggest that European firms do not vary the average number of hours worked in response to short-run fluctuations in demand in a systematic way. A potential explanation could be that adjustments in Europe take place by changing the number of temporary workers instead of average hours per worker. A more complete answer, however, would need further research. Given these estimates though, we turn to the question of whether the estimated models help reduce the cyclicality of the productivity residuals.

Cyclicality of productivity growth

Basu and Fernald (2001) estimate a similar model to Basu *et al.* (2001) and use the results to look at the cyclicality of productivity growth. As is the case with traditional growth accounting, productivity growth is a residual. When the regression results presented above are used to account for non-constant returns to scale and corrected for unmeasured input utilization, the residuals from this regression give an adjusted productivity growth measure. This adjusted measure will be a more accurate measure of technical change than TFP growth, but as it is a residual, there may still be other factors included as well. Basu and Fernald (2001) show that the traditional Solow residual (assuming constant returns to scale and well-measured inputs) is positively correlated with output growth while the residuals from their regression are not.[161]

Although most of the estimates show returns to scale that are statistically indistinguishable from constant and few significant utilization effects, the point

[160] Appendix Table 5.A6 shows the same estimation results using Hall-Ramey instruments. These specifications show a few more significant utilization effects, but also more significantly decreasing returns to scale.

[161] In general, technical change from these regressions is equal to the constant plus the residual. However, average technical change is not relevant for the cyclicality of technical change.

estimates can be used to see whether these can decrease the observed procyclicality. To compare the results from this analysis to those in Basu and Fernald (2001), it is useful to start at the aggregate level of the market economies. Basu *et al.* (2001) calculate aggregate adjusted productivity growth by aggregating industry-level residuals. However, since these residuals are based on a gross output production function, an adjustment needs to be made to deal with the double counting of output. Following Rotemberg and Woodford (1995), a value added-based productivity growth measure can be calculated as:

$$dA_i^V = \frac{dA_i}{1-\gamma s_{Mi}}. \tag{5.8}$$

In this equation, dA_i is the residual from either (5.6a) or (5.6b). This residual is adjusted using the returns to scale estimate γ and the share of materials in gross output s_{Mi} of the industry in question. The value added-based productivity residuals can then be aggregated across industries using the industry's share in value added. These residuals are then correlated with value added growth for broad sectors or the market economy.

Table 5.6 presents the evidence on the cyclicality of the productivity residuals in three panels. Panel A shows the correlations for the market economy, excluding agriculture and mining for different specifications. Panel B shows correlations for each industry group, based on the residuals of the models presented in Table 5.5. Panel C shows the number of industries within each industry group with significantly positive correlations.

Table 5.6 Correlation between output growth and adjusted productivity growth for industry groups under variable returns to scale and corrected for unmeasured utilization

	France	Germany	Netherlands	U.S.
A: Output/productivity correlations: different specifications				
Market economy excluding agriculture & mining				
Constant returns to scale	0.64*	0.71*	0.44*	0.51*
Variable returns to scale	0.59*	0.14	0.18	0.33
Variable returns to scale & utilization correction	0.37	0.15	-0.09	0.21
B: Output/productivity correlations, industry groups				
Market economy	0.73*	0.16	0.67*	0.20
Market economy excluding agriculture & mining	0.37	0.15	-0.09	0.21
Durable manufacturing	0.38	0.43*	0.65*	0.38
Non-durable manufacturing	0.73*	0.40	0.69*	0.86*
Non-manufacturing	0.89*	0.87*	0.76*	0.54*
Services	0.79*	0.62*	0.32	0.50*
C: Number of industries with significantly positive correlations (5% level)				
Market economy (25 industries)	16	7	17	5
Market economy excluding agriculture & mining (23)	12	6	12	4
Durable manufacturing (6)	3	2	3	1
Non-durable manufacturing (7)	5	1	2	5
Non-manufacturing (12)	12	9	9	4
Services (10)	8	6	7	4

Note: Top panel: correlations between output growth and technical change residuals from the regressions in Tables 5.3 to 5.5. * denotes a correlation significantly greater than zero at the 5% level. Bottom panel: number of industries with significantly non-zero correlations/number of industries in group. See Table 5.A3 for definitions of industry groupings.

As Panel A shows, at the aggregate level the Basu-Fernald (2001) model reduces the procyclicality of the technical change residuals, with correlations becoming mostly insignificant when allowing for variable returns to scale (Table 5.3) and correlations dropping even further when the utilization proxy is included (Table 5.5). The evidence is more mixed when looking at the main industry groups in Panel B. Although the aggregate correlations have become insignificant, in each of the countries three out of four industry groups still show a significantly positive correlation between output growth and technical change. This result casts some doubt on the scope of the Basu and Fernald (2001) results.[162] These doubts become even stronger when looking at the cyclicality of individual industries. Hart and Malley (1999) have shown that in general, there is important heterogeneity in the cyclicality of productivity across industries, making it an important issue to examine.

[162] They show comparable correlations only for the private economy and the overall manufacturing sector.

Panel C of Table 5.6 shows the number of industries where the correlation is significantly different from zero.[163] In most groupings a considerable fraction of industries shows a significant positive correlation, even in cases where the industry group as a whole shows no sign of procyclicality anymore. Appendix Table 5.A7 shows that this finding remains, even when allowing all coefficients to vary across industries.

Table 5.7 Share of U.S. industries with significantly positive correlation between output growth and adjusted productivity growth for various specifications

Specification	*Market economy*	*Market economy excl. agriculture & mining*
Baseline (downstream indicators, industry dummies)	40%	43%
Hall-Ramey instruments (industry dummies)	68%	65%
Basu *et al.* (2001, Table 1) parameters		26%
Single constant (downstream indicators)	32%	35%
Time dummies (downstream indicators)	64%	52%
Industry and time dummies (downstream indicators)	76%	65%

Notes: shows percentage of U.S. industries where the technical change residual is significantly positively correlated with output growth. Different coefficients are estimated for durable manufacturing, non-durable manufacturing and non-manufacturing or services. The numer of industries with significant correlations is added across sectors and divided by the total number of industries in the sector (25 for the market economy, 23 if agriculture and mining are excluded).

To further evaluate the robustness of this finding, Table 5.7 shows the share of industries with significantly positive correlations in the U.S. for a number of alternative specifications.[164] The set-up is the same as for Table 5.6: coefficients are allowed to vary across broad industry groups, but for brevity, the number of significant correlations is added across groups. For example, the 40 percent in the first cell of the table is calculated by adding the one durable manufacturing industry, five non-durables and four non-manufacturing industries with significant positive correlations, divided by the maximum of 25 industries in the market economy. Five different specifications are considered, first the Hall-Ramey instruments, as discussed in Table 5.2, are used instead of the downstream indicators. Second, the parameters from the Basu *et al.* (2001) study are used to calculate the residuals. The last three specifications first drop the industry dummies and include only a single constant, next include year dummies and finally include both year and industry dummies. The main result is that irrespective of the specification, a noticeable fraction of industries still shows significantly positive correlations between output growth and the technical

[163] After the name of the industry grouping, the total number of industries in that group is shown in brackets.
[164] The results for other countries are very similar.

change residuals. Although not shown here, the significant correlations can be found across all industry groups. When using the Basu *et al.* (2001) parameters, the fraction of significant correlations drops to 26 percent but this is still more than could be expected based on random chance. In all, this raises serious questions about the ability of the Basu and Fernald (2001) model to explain the observed cyclicality of productivity growth, especially when looking at individual industries and European countries.

Adjusted productivity growth

Up to here, the focus of the analysis has been on the cyclicality of technical change residuals. A related question is to what extent the estimated models affect the stylized productivity growth facts that were presented in the previous chapter. The results in the previous chapter all relied on standard growth accounting assumptions of constant returns to scale and well-measured inputs. The estimates in Table 5.5 show that these assumptions are not uniformly supported by the data, so it is useful to see the effect of relaxing these assumptions on productivity growth estimates. Table 5.8 shows two different productivity growth estimates for the period 1995-2003 for both the market economy and the market economy, excluding agriculture and mining. In addition, the contribution of market services to aggregate growth is shown. To make it easier to compare the results to those presented in the previous chapter, the parameters from Table 5.5 are applied on a value added basis, instead of in a gross output framework. Hence the parameters from Table 5.5 are converted to a value added basis:

$$\gamma^V = \gamma \frac{1 - s_{Mi}}{1 - \gamma s_{Mi}} . \tag{5.9}$$

Equation (5.9) shows how the returns to scale parameter is converted from gross output to value added and the same equation is used for the utilization parameter.

Table 5.8 Productivity growth relaxing growth accounting assumptions

	Market economy		*Market economy excluding agriculture & mining*	
	Solow	Adjusted	Solow	Adjusted
Average TFP growth, 1995-2003				
France	0.79	1.25	0.76	1.04
Germany	0.88	0.91	0.84	0.77
Netherlands	0.14	0.10	0.14	-0.36
U.S.	1.78	1.86	1.76	1.64
Contribution of market services, 1995-2003				
France	-0.18	0.33	-0.19	0.13
Germany	0.14	0.10	0.14	0.01
Netherlands	-0.19	-0.22	-0.20	-0.70
U.S.	0.93	1.03	0.96	0.87

Notes: The columns labelled 'Solow' show productivity growth under constant returns to scale and without utilization adjustments. 'Adjusted' applies the estimated returns to scale and utilization correction from Table 5.5, adjusted to a value added basis.

The columns labelled ‘Solow’ show (total factor) productivity growth under the assumptions of constant returns to scale and well-measured inputs. The ‘Adjusted’ columns apply the returns to scale parameters and utilization correction from Table 5.5 for the main industry groups.[165] As Table 5.8 show, the adjustment are sometimes sizeable with adjusted productivity growth coming out half a percentage point lower in the case of the market economy excluding agriculture and mining in the Netherlands. In contrast, growth is almost half a percentage point higher in the case of the market economy in France.

However, the adjustments have no large impact on the main stylized facts from the previous chapter. The U.S. shows the highest aggregate growth for this group of countries after 1995. Similarly, market services make much larger contributions to aggregate growth in the U.S. than in the European countries. It is also important to note the effect of excluding agriculture and mining. Germany and the U.S. provide the clearest cases with growth compared to the Solow residual coming out higher if agriculture and mining are included and lower when they are excluded. Also, in some sense the adjustments represent an upper-bound since for most industry groups and countries, the returns to scale were not significantly different from one, and the utilization adjustment statistically indistinguishable from zero.

[165] Nearly all of the difference in average growth can be traced to the effect of applying the returns to scale parameters.

5.6 Concluding remarks

It is important to understand why productivity growth is procyclical, both for understanding the determinants of the business cycle and productivity growth. This chapter extends the current literature by not only analyzing this phenomenon for the U.S. but also for France, Germany and the Netherlands using an up-to-date and internationally consistent dataset covering the entire market economy. The analysis follows the approach of Basu and Fernald (2001). Production functions are estimated to allow for non-constant returns to scale and unmeasured input utilization. While this study is not the first to analyze this issue for countries outside the U.S., none of the earlier studies have followed Basu and Fernald (2001) and tested whether the estimated models lead to lower correlation between growth of output and the adjusted productivity residual using the production model estimates. Furthermore, industry-specific demand-side instruments are introduced to correct for simultaneity bias in the estimation of production functions.

The results cast some doubt on the ability of the Basu and Fernald (2001) model to account for procyclical productivity growth beyond their specific case. At the level of the market economy (excluding agriculture and mining), the correlation between adjusted productivity growth and output growth is no longer significant. But in some individual industry groups, technical change is still significantly procyclical. Furthermore, the results show that in all countries, a sizeable fraction of individual industries show procyclical productivity. Since the underlying theoretical model tries to explain firm behaviour, the failure of the empirical model in many industries is particularly worrisome.

There have been other studies that cast doubt on the popular explanations for procyclical productivity growth. Basu and Fernald (1997) themselves raised questions about the prevalence of increasing returns to scale in the U.S., while Sbordone (1997) showed that the dynamic behaviour of output and productivity is not consistent with externalities. The main justification for looking at input utilization is the presence of adjustment costs for labour and capital. However, in recent work, Hall (2004) finds strong evidence against important adjustment costs to labour and capital over a time horizon of a year or more. As a result, it is not clear whether firms will vary utilization very much in response to shocks at the frequency for which we observe the data. The finding of Baily, Bartelsman and Haltiwanger (2001) that long-run downsizing plants show more procyclicality during downturns than upsizing plants also argues against the input utilization hypothesis. In their view, downsizing establishments would have fewer incentives to hoard labour or conserve capital. This chapter provides some direct evidence that unmeasured input utilization is unable to account for procyclical productivity growth in many settings. One possible reason for this may be that average hours worked per person is not a very good proxy for unmeasured input utilization in most industries, especially outside the U.S. and in the services sector.

This raises the question where to go from here. One avenue might be to try and find better measures for unmeasured input utilization, especially outside manufacturing. For example, the type of customers of an industry (business versus consumers) may be important, as Hart and Malley (1999) find less evidence of procyclicality in investment-goods industries than in other industries. More theoretical research may also provide useful new directions for empirical research. Ultimately, firm-level studies, especially extending the work of Baily, Bartelsman and Haltiwanger (2001) beyond U.S. manufacturing, may be needed to understand how firms adjust to changing demand.

More encouraging are the results on the robustness of the stylized productivity growth facts. Relaxing the assumptions of constant returns to scale and well-measured inputs has a noticeable impact on productivity growth estimates. However, the stylized facts from Chapter 4 are not affected. U.S. TFP growth remains higher than in the European countries, especially in market services. Furthermore the regression parameters, and therefore the adjusted productivity estimates, are strongly affected by relatively minor changes to the data, such as excluding agriculture and mining from the set of industries. This suggests that relaxing some of the growth accounting assumptions may be warranted by the data, but it can give a false sense of precision. A more robust approach is to acknowledge that total factor productivity growth is a concept that captures many different phenomena, such as technical change and returns to scale.

Appendix 5.A Appendix tables

Appendix Table 5.1 Correlation between annual output growth and total factor productivity growth at the industry level, France, Germany, Netherlands and U.S., 1979-2003

	France	Germany	Netherlands	US
Agriculture, forestry and fishing	0.82*	0.74*	0.65*	0.84*
Mining and quarrying	0.74*	0.48*	0.46*	0.19
Food products	-0.22	0.08	0.38	0.28
Textiles, clothing and leather	0.29	0.62*	0.32	0.40
Wood products	0.52*	0.71*	0.34	0.39
Paper, printing and publishing	0.05	0.63*	0.68*	0.34
Petroleum and coal products	0.57*	0.52*	0.42*	-0.19
Chemical products	0.84*	0.44*	0.63*	0.45*
Rubber and plastics	-0.04	0.33	0.40	0.45*
Non-metalic mineral products	0.38	0.88*	0.48*	0.57*
Metal products	0.16	0.54*	0.83*	0.7*
Machinery	0.68*	0.63*	0.77*	0.69*
Electrical and electronic equipment & instruments	0.58*	0.29	0.13	0.69*
Transport equipment	0.63*	0.53*	0.67*	0.19
Furniture and miscellaneous manufacturing	0.66*	0.64*	0.19	0.56*
Electricity, gas and water	0.65*	0.82*	0.40	0.27
Construction	0.60*	-0.14	0.22	0.56*
Wholesale trade	0.33	0.49*	0.76*	-0.17
Retail trade	0.73*	0.73*	0.70*	0.56*
Hotels and restaurants	0.39	0.67*	0.72*	0.06
Transport & storage	0.53*	0.55*	0.80*	0.24
Communications	0.35	0.60*	0.71*	0.55*
Financial intermediation	0.23	0.53*	0.55*	0.02
Business services	0.06	0.76*	0.17	0.07
Other services	0.57*	0.37	0.64*	0.47*
Market economy	0.66*	0.69*	0.62*	0.57*

Note: Total factor productivity growth is calculated as growth of gross output minus growth of a Törnquist aggregate of intermediate inputs, capital and labour.

Appendix Table 5.2 F-statistics for the first-stage regression of instruments on input growth

	France	Germany	Netherlands	US
Agriculture, forestry and fishing	3.31	9.59*	0.75	2.31
Mining and quarrying	2.81	8.73	0.29	0.55
Food products	15.9**	1.19	8.28	3.92
Textiles, clothing and leather	12.4*	17.9**	9.99*	7.54
Wood products	1.87	1.07	2.29	8.92
Paper, printing and publishing	15.7**	24.9**	8.36	7.59
Petroleum and coal products	4.27	2.97	1.07	2.40
Chemical products	16.9**	4.94	7.03	5.84
Rubber and plastics	2.54	17.9**	16.3**	23.6**
Non-metalic mineral products	10.6*	0.88	1.71	8.58
Metal products	7.19	20.5**	4.12	6.93
Machinery	8.49	15.1**	24.8**	7.47
Electrical and electronic equipment & instruments	14.8**	23.9**	29.1**	15.8**
Transport equipment	25**	9.58*	6.13	9.90*
Furniture and miscellaneous manufacturing	0.66	2.08	8.22	8.74
Electricity, gas and water	7.58	10.8*	9.83*	0.23
Construction	7.78	5.73	13.4*	4.48
Wholesale trade	30.3**	7.93	30.6**	5.12
Retail trade	16.8**	15.8**	22.6**	15.6**
Hotels and restaurants	22.8**	42.0**	8.40	27.1**
Transport & storage	18.0**	4.34	14.1**	28.1**
Communications	10.6*	2.68	18.5**	20.4**
Financial intermediation	8.02	5.58	47.3**	4.48
Business services	63.3**	32.9**	54.8**	66.3**
Other services	67.3**	8.91	15.9**	38.6**
Market economy	15.8**	11.9*	14.5**	13.2*

Note: *: bias is less than 10% of OLS bias, **: bias is less than 5% of OLS bias

Instruments are the current value and one lag of industry-specific downstream indicators. Significance is determined using critical values from Table 1 of Stock and Yogo (2004). Critical 5% value is 13.91, the 10% value is 9.08.

Appendix Table 5.3 Estimates of returns to scale of inputs for individual industries, 1979-2003

	Ind. Group	France	Germany	Netherlands	US
Agriculture, forestry and fishing	NMFG	1.55	0.88	0.74	1.15
Mining and quarrying	NMFG	-2.48	0.61	-0.21	-1.64*
Food products	NDUR	0.46*	0.59	0.3	1.35
Textiles, clothing and leather	NDUR	1.85	1.19*	1.01	1.24
Wood products	NDUR	1.04	1.15	0.87	0.92
Paper, printing and publishing	NDUR	1.04	1.15	1.29*	1.23
Petroleum and coal products	NDUR	0.62	1.23	0.97	0.45*
Chemical products	NDUR	1.68*	1.15	0.76	1.21
Rubber and plastics	NDUR	1.06	1.04	1.18	1.22*
Non-metalic mineral products	DUR	0.96	1.54*	1.62	1.21*
Metal products	DUR	1.05	1.08	1.31*	1.27*
Machinery	DUR	1.32	1.15*	1.28*	1.23*
Electrical and electronic equipment & instruments	DUR	1.20*	0.94	1.03	1.42
Transport equipment	DUR	1.25*	1.09	1.15*	1.00
Furniture and miscellaneous manufacturing	DUR	1.57	1.30*	0.88	1.40
Electricity, gas and water	SER/NMFG	0.12*	0.84	1.08	0.43
Construction	SER/NMFG	1.25*	0.93	1.01	1.07
Wholesale trade	SER/NMFG	0.93	1.46*	1.34*	1.10
Retail trade	SER/NMFG	0.25	1.67*	1.35	1.33
Hotels and restaurants	SER/NMFG	1.28	1.49	1.47	0.74
Transport & storage	SER/NMFG	1.21	1.30*	1.36*	0.81*
Communications	SER/NMFG	0.99	1.12	0.93	0.61
Financial intermediation	SER/NMFG	0.83	0.88	0.42*	1.21
Business services	SER/NMFG	0.96	1.37*	1.07	0.96
Other services	SER/NMFG	0.83	1.25	2.47	1.20
Market economy		1.15*	1.09	1.01	1.11*

Ind. Group denotes the group in which the industry is included. DUR = Durable manufacturing, NDUR = Non-durable manufacturing, SER = Services, NMFG = Non-manufacturing.

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs as independent variable; a constant was also included. Estimation is done industry-by-industry using two-stage least squares with the current value and one lag of the downstream indicator for each industry as instruments. Standard errors, consistent for heteroscedasticity and autocorrelation, are shown in parentheses. * denotes parameters significantly different from one at the 5% level.

Appendix Table 5.4 Estimates of returns to scale of inputs without a utilization correction, using Hall-Ramey instruments, 1979-2003

	Hall-Ramey instruments			
	France	Germany	Netherlands	US
Market economy	0.99	0.85*	1.11	0.90*
	(0.06)	(0.04)	(0.07)	(0.04)
Market economy excluding agriculture & mining	0.97	0.98	1.12*	0.94
	(0.06)	(0.04)	(0.04)	(0.04)
Durable manufacturing	1.08*	0.94	1.07	1.13*
	(0.03)	(0.05)	(0.05)	(0.05)
Non-durable manufacturing	0.87	1.05	1.06	0.88
	(0.13)	(0.05)	(0.04)	(0.07)
Non-manufacturing	0.72*	0.82*	1.08	0.69*
	(0.1)	(0.07)	(0.06)	(0.05)
Services	0.52*	0.99	1.11	0.72*
	(0.09)	(0.08)	(0.06)	(0.04)

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs as independent variable. Estimation is done for a panel of industries, with industry fixed effects included (not shown) using two-stage least squares with the current value and one lag of the real oil price and real government spending as instruments. Parameters in the first stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and autocorrelation, are shown in parentheses. * denotes parameters significantly different from one at the 5% level. See Table 5.A3 for definitions of industry groupings.

Appendix Table 5.5 Returns to scale of inputs with a correction for unmeasured input utilization using Hall-Ramey instruments, 1979-2003

	Hall-Ramey instruments			
	Returns to scale			
	France	Germany	Netherlands	US
Market economy	1.00	0.87	1.11	0.86*
	(0.06)	(0.08)	(0.06)	(0.06)
Market economy excluding agriculture & mining	0.96	1.07	1.11*	0.93
	(0.07)	(0.07)	(0.04)	(0.06)
Durable manufacturing	1.12*	0.98	1.06	1.11
	(0.02)	(0.08)	(0.04)	(0.06)
Non-durable manufacturing	0.88	1.05	1.06	0.88
	(0.08)	(0.06)	(0.04)	(0.07)
Non-manufacturing	0.73*	0.82	1.08	0.68*
	(0.12)	(0.10)	(0.07)	(0.06)
Services	0.54*	1.02	1.11	0.74*
	(0.14)	(0.08)	(0.06)	(0.06)
	Utilization correction			
Market economy	0.04	-0.15	0.02	0.39*
	(0.23)	(0.19)	(0.11)	(0.19)
Market economy excluding agriculture & mining	0.11	-0.51*	-0.13	0.11
	(0.24)	(0.22)	(0.07)	(0.20)
Durable manufacturing	-0.40*	-0.28	-0.21*	0.18
	(0.11)	(0.36)	(0.05)	(0.25)
Non-durable manufacturing	-0.08	-0.26	-0.05	0.12
	(0.15)	(0.24)	(0.07)	(0.16)
Non-manufacturing	-0.24	-0.28	0.01	0.19
	(0.13)	(0.16)	(0.15)	(0.19)
Services	-0.27	-0.63*	-0.17	-0.21
	(0.15)	(0.14)	(0.09)	(0.19)

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs and growth of average hours worked as independent variable. Parameters are estimated for a panel of industries, with industry fixed effects included (not shown). Parameters are estimated using two-stage least squares with the current value and one lag of the real oil price and real government spending as instruments. Parameters in the first stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and auto correlation, are shown in parentheses. * denotes parameters significantly different from one (returns to scale) or zero (utilization correction) at the 5% level. See Table 5.A3 for definitions of industry groupings.

Appendix Table 5.6 Returns to scale of inputs with a correction for unmeasured input utilization, excluding average hours worked from aggregate input growth using Hall-Ramey instruments, 1979-2003

	Hall-Ramey instruments			
	Returns to scale			
	France	Germany	Netherlands	US
Market economy	0.99	0.88	1.12	0.87*
	(0.06)	(0.08)	(0.05)	(0.06)
Market economy excluding agriculture & mining	0.95	1.07	1.13*	0.94
	(0.07)	(0.07)	(0.04)	(0.06)
Durable manufacturing	1.12*	0.98	1.07	1.11
	(0.02)	(0.08)	(0.04)	(0.06)
Non-durable manufacturing	0.88	1.05	1.07	0.89
	(0.08)	(0.06)	(0.04)	(0.07)
Non-manufacturing	0.73*	0.82	1.08	0.69*
	(0.12)	(0.10)	(0.05)	(0.06)
Services	0.54*	1.02	1.14*	0.76*
	(0.14)	(0.09)	(0.06)	(0.06)
	Utilization correction			
Market economy	0.33	0.12	0.26*	0.61*
	(0.22)	(0.19)	(0.1)	(0.18)
Market economy excluding agriculture & mining	0.4	-0.17	0.15*	0.39*
	(0.23)	(0.22)	(0.06)	(0.19)
Durable manufacturing	-0.09	0.02	0.06	0.53*
	(0.1)	(0.38)	(0.05)	(0.24)
Non-durable manufacturing	0.1	-0.02	0.1	0.31*
	(0.14)	(0.27)	(0.05)	(0.14)
Non-manufacturing	0.01	0.00	0.32*	0.38*
	(0.12)	(0.16)	(0.14)	(0.18)
Services	-0.08	-0.24	0.25*	0.05
	(0.14)	(0.13)	(0.08)	(0.17)

Notes: Table shows parameter estimates from a regression with output growth as the dependent variable and growth of inputs and growth of average hours worked as independent variable. The growth of inputs is modified to exclude growth in average hours worked. Parameters are estimated for a panel of industries, with industry fixed effects included (not shown). Parameters are estimated using two-stage least squares with the current value and one lag of the real oil price and real government spending as instruments. Parameters in the first stage regression are allowed to vary across industries. Standard errors, consistent for heteroscedasticity and auto correlation, are shown in parentheses. * denotes parameters significantly different from one (returns to scale) or zero (utilization correction) at the 5% level. See Table 5.A3 for definitions of industry groupings.

Appendix Table 5.7 Correlation between output and adjusted productivity growth, based on industry-by-industry estimates of returns to scale and unmeasured input utilization

	France	Germany	Netherlands	US
Market economy				
Constant returns to scale	0.66*	0.69*	0.62*	0.57*
Variable returns to scale	-0.01	0.21	0.53*	0.21
Variable returns to scale & utilization correction	-0.34	-0.09	0.35	0.19
Number of market industries with correlation significantly different from zero (5% level)				
Constant returns to scale	13	20	15	11
Variable returns to scale	10	8	8	8
Variable returns to scale & utilization correction	5	7	8	7

Note: correlations between output growth and technical change residuals. * denotes a correlation significantly different from zero at the 5% level. The definitions of technical change residuals is similar to Table 5.6, only in this table the parameters are allowed to vary for each industry.

Chapter 6 Summary and Conclusions

6.1 Introduction

In the coming decades, European countries face a number of major economic challenges, such as dealing with ageing populations and increased competition from both the United States and low-wage countries such as India and China. Facing these long-run challenges motivates the need to strengthen European competitiveness. Indeed two of the main economic projects of the European Union are geared towards this goal. In 1999, twelve countries joined the Economic and Monetary Union (EMU), with the aim of stimulating economic integration and growth. In 2000, EU governments subscribed to the Lisbon agenda of reforms to improve competitiveness. This study has analyzed the prospects of both projects from different perspectives.

Chapters 2 and 3 focused on the challenges for the new common monetary policy in the euro area in relation to the business cycles in European countries. Chapters 4 and 5 looked at the driving forces of productivity growth in Europe relative to the United States. This chapter first summarizes the main results from each chapter, before discussing the implications for economy policy in more detail. To face Europe's competitiveness challenges, the research in this study suggests that a broad reform agenda is needed, aimed at making European economies more flexible.

6.2 Prospects for a common currency

The scale and scope of the euro experiment have been emphasized frequently. Twelve countries with over 300 million inhabitants have given up their national currency and adopted a common monetary policy. This has created an economic area that is second only to the United States (in terms of GDP), in which a new central bank, the ECB, is responsible for monetary policy. Naturally, such an endeavour faces challenges, both in the short run and in the long run.

In the short run, the ECB has to establish a common monetary policy that fits a heterogeneous group of countries. Although the ECB has some tools, like structural models, to guide its policy, a euro area business cycle index can be a useful complement. Such an index aims to combine the information from a number of economic variables into a single figure reflecting current economic activity. The component variables should normally be available at least once a month and are used complement the GDP figures which are only available on a quarterly basis and which are mostly subject to large revisions. An important question is how to select the variables that go into the index and how to construct the business cycle index. One approach is to collect a dataset that is as large and diverse as possible and use a statistical model to determine the importance of each of the variables. Alternatively, analysts select a limited set of variables by judging how well their development corresponds to GDP.

Chapter 2 compares a set of business cycle indexes which are based on these two different approaches. As it turns out, there is little difference in the ability of the indexes to capture the main cyclical facts of the euro area. However, as it is easier to interpret changes in an index based on less than forty variables than in one based on 250 variables, the approach where analysts select a set of variables has certain merits. The second part of the analysis in Chapter 2 showed how variables from only three euro area countries (France, Germany and Spain) can provide a good insight into the euro area business cycle. Whenever the euro area was in a recession, variables from each of the three countries also pointed towards contraction. This suggests that at least in the short run, heterogeneity in the euro area is not as large that it will hamper monetary policy making. However, another finding is that comparable variables in different countries have different effects. For example, German industrial production is much more important in explaining movements in euro area GDP than comparable series for France and Spain.

This hints at the main long run challenge to the sustainability of the currency area. If business cycles differ across countries, monetary policy will be too strict for countries with below-average growth and too accommodating for countries with above-average performance. This is potentially worrisome since cyclical differences have led to the break-up of currency unions in the past. Chapter 3 argues that the prospects for the euro area depend on the future similarity of business cycles and the degree of flexibility of labour markets. In recent decades economic and monetary integration within Europe has increased and business cycle synchronization among EMU members has increased modestly. However, this mild upward trend hides substantial variation over time. The experience of states within the U.S. suggests that such variation is unlikely to disappear as a result of further economic integration. Indeed, fluctuations in synchronization over time are stronger within the U.S. than within Europe and these fluctuations appear closely related to major national cyclical episodes. For example, during the Great Depression and the wartime boom, synchronization between U.S. states was high, but after World War II, average synchronization decreased.

To better understand how the EMU is likely to affect synchronization within the euro area, a set of determinants is identified. The analysis confirms earlier results that countries with closer trade links have more similar business cycles. The other findings are less well established in other research. Countries with more similar monetary and fiscal policies, highly correlated stock market returns, stable exchange rates, and a larger share of intra-industry trade also show higher output correlations. Furthermore, these other factors are at least as important as trade in terms of their impact on synchronization.

Based on this analysis, it seems likely that synchronization will increase as a result of the EMU. The most obvious reason for this is the common monetary policy and fixed exchange rates under monetary union. However, since the 1970s, stock market returns have become more similar and the share of intra-industry trade has risen too. The main uncertainties are the future course of fiscal policy and the degree of specialization. If a country embarks on a unilateral spending spree, its business cycle will less resemble those in other EMU countries. However, if all countries simultaneously break the deficit rule of the Stability and Growth Pact, fiscal policy will remain highly correlated. The more qualitative prescription that the budget should be in balance over the cycle can help to achieve a greater degree of synchronization

Specialization is the other uncertain factor in the future development of synchronization. The analysis showed that countries with a more similar industrial and trade structure have more similar business cycles. Krugman (1991) expects regions (countries) to specialize as a result of economic integration due to agglomeration benefits. However, the empirical evidence is mixed. The dataset used in Chapter 3 shows that since the early 1970s, export bundles have become more similar and the intra-industry share has risen between euro area countries, while the measures of industrial similarity show increasing specialization over time. Evidence for U.S. regions by Kim (1995) suggests that agglomeration effects have not been a major factor in driving specialization in the U.S. Instead, since the 1930s, the industrial structure of U.S. regions has become more similar due to more mobile production factors. This suggests that industrial similarity across Europe might increase due to greater cross-border labour market flexibility.

Although the costs of the euro are likely to remain low due to sufficiently high synchronization of business cycles, the uncertainties regarding fiscal policy coordination and changes in specialisation patterns make the future degree of synchronization uncertain too. One way to mitigate this uncertainty is to increase flexibility and especially make cross-border movements of labour much more straightforward. First of all, a greater degree of flexibility is likely to lead to more similar cycles due to a decrease in specialization. Second, when a country is hit by an asymmetric shock, workers can move to countries with higher labour demand if labour markets are sufficiently flexible. This in turn will mitigate the effects of the asymmetric shock, reducing the need for other policy measures. Furthermore, apart from dampening the effect of asymmetric shocks, more flexible labour markets can also stimulate productivity growth.

6.3 What drives productivity growth?

The analysis in Chapters 2 and 3 provides insight into the role of certain structural features of the European economies for European business cycles. Chapters 4 and 5 focus on the question of whether structural or cyclical factors drive the productivity growth gap between Europe and the U.S. As U.S. labour productivity growth has been considerably higher than in Europe since the mid 1990s, the question arises whether the European economies are sufficiently competitive and innovative to safeguard future living standards.

It is argued here that the main structural explanation for Europe's lagging productivity growth since the 1990s is the smaller impact of new information and communication technologies (ICT) compared to the U.S. This is not so much due to a larger ICT producing sector, but mainly due to less extensive and less productive use of ICT across the economy in European countries. Even though the larger ICT producing sector is one factor in the EU-U.S. growth differential, it makes a relatively small contribution to this growth differential. In fact while the ICT manufacturing sector contributes more to labour productivity growth in the U.S. than in Europe, the opposite is the case in the ICT producing services sector, which includes telecommunications. The big difference between Europe and the U.S. is in the pace of ICT investment and its productive use. It is relatively straightforward to determine that European ICT investment is lower than in the U.S., but harder and more controversial to establish its productive impact.

In theory, the marginal returns to ICT investment should equal its marginal cost. ICT goods can readily be purchased on international markets, so in a competitive economy, the returns from investing in ICT will be driven down to marginal cost. On average, the equality of marginal returns and marginal cost on ICT cannot be rejected with the industry data used here. But this average return hides important variation over time. While the productivity of ICT investment up to the beginning of the 1980s and again since the early 1990s was in line with marginal cost, returns on ICT were lower than marginal cost during the 1980s. The evidence suggests that this U-shaped pattern of returns to ICT was apparent in both the Anglo-Saxon countries (UK and U.S.) and the Continental European countries (France, Germany and the Netherlands) in the analysis. However, the U-shaped pattern for the Anglo-Saxon countries preceded that of the Continental European countries by a number of years

One explanation for these patterns is that ICT investment can at first quickly generate important productivity gains (the so-called ‘hard savings’). However, additional gains (the ‘soft savings’) from ICT use can only be exploited once sufficient time and money have been invested in complementary innovations. Many of these organizational investments are often not measured as investment but as expenses, leading to an understatement in TFP growth.[166] As these intangible investments start to bear fruit, TFP growth rises again.

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[166] See Basu *et al.* (2004) for an economic model incorporating unmeasured investments.

In Chapter 4, we find that ICT mostly generates productive returns in line with marginal cost. However, strong TFP growth in a number of specific U.S. market services (in particular in trade and finance) suggests that the ICT gains may be larger. A reason for this could be that traditionally, services have not been very standardized, either in the set of inputs purchased or in 'bundles' of services that are sold, lowering its potential for productivity growth.[167] However, ICT has become a helpful tool for codifying knowledge about, for example, consumer buying patterns. Such information can then be analyzed to allow for greater standardization and hence drive productivity improvement.

Elucidating the link between knowledge, codification and ICT is one avenue for future research. Another approach is to establish the link between firm-level studies of the impact of ICT (e.g. OECD, 2004) and the type of industry-level analysis presented in this study. A number of firm-level studies find that the returns from ICT are larger than their marginal cost. In other words, they find evidence of positive ICT spillovers. However, the industry-level results presented here suggest that returns are equal to cost (at best). The explanation for this difference may also be related to intangible investments. The return to intangible investments is likely to be much more uncertain than the return to tangible investment and the type of investment will differ by industry. As a result, some firms in an industry will be successful in generating positive spillovers, while other firms will fail and may even generate negative spillovers. Although the competitive process will favour the successful firm, the unsuccessful firm will not disappear quickly in particular not when labour and bankruptcy laws are rigid. More research is needed to establish how this type of averaging-out of performance at firm level takes place in practice and how it affects the industry aggregate.

In addition to structural factors, cyclical factors may also be important in explaining the productivity growth gap between Europe and the U.S. The fact that productivity growth is faster during periods of strong economic growth and slower in recessions is interesting, but causality may run either way. Productivity shocks could cause business cycles but demand-side factors may also influence (measured) productivity. If the second explanation holds, a growth comparison between countries

[167] See Boden and Miles (2000) for more on the distinction between manufacturing and services.

will depend on the state of the business cycle in each country. Specifically, economic activity boomed in the late 1990s in the U.S., but much less so in Europe. Although the U.S. experienced a (relatively mild) recession in 2000-2001, U.S. productivity growth continued to outpace European growth, which suggests that cyclical factor cannot explain the entire EU-U.S. growth gap.[168]

Understanding the reasons behind the cyclicality of productivity can help in interpreting productivity growth in the short run, as well as in understanding the business cycle. Two popular demand-side explanations for cyclical productivity are the possibility of increasing returns to scale and unmeasured input utilization. Chapter 5 tests the importance of both for three European countries (France, Germany and the Netherlands) and the U.S. Earlier research proposed two criteria for testing these explanations (Basu and Fernald, 2001). First, the hypotheses of constant returns and well-measured input utilization should be rejected based on production function estimates. Second, productivity growth at the aggregate level should no longer be correlated with output growth after adjusting for non-constant returns to scale and unmeasured inputs.

However, the Basu and Fernald (2001) model aims to explain firm-level behaviour. This suggests that the model should be tested at the most detailed level possible. In Chapter 5, industry data are used, so a more appropriate test of the Basu-Fernald model is whether the correlation between output and productivity growth decreases at the industry level. The analysis based on this model suggests that increasing returns and unmeasured input utilization are indeed able to explain aggregate cyclicality. However, in many industries, adjusted productivity growth remains positively correlated with output.

This raises questions about the usefulness of the Basu-Fernald (2001) model. The importance of increasing returns was reduced by using the change in average hours worked as a proxy for unmeasured input utilization. The reasoning behind this proxy is that in times of high demand, firms will increase average hours worked as well as worker effort and capital utilization. In the long run, new workers can be hired and new capital equipment installed. However, if work effort is less related to the use of machinery such as in services, the proxy may be less useful. Also, working hour regulations may make

[168] Inklaar and McGuckin (2003) also showed that averaged over 1995-2000, cyclical factors were not very important.

this measure less informative outside the U.S. In the more regulated European labour markets, it may be easier to hire temporary workers instead of adjusting average working hours. This suggests more research into measuring input utilization may be helpful.

The analysis in Chapter 5 also serves as a test for some of the well-known and frequently criticized growth accounting assumptions, namely constant returns to scale and well-measured inputs. Even when taking the estimation results from the cyclical analysis at face value, the main stylized productivity growth facts (in particular the slowdown of European productivity growth relative to the U.S. since the mid-1990s) are not affected by relaxing these assumptions. Furthermore, the size and even the sign of the adjustments to productivity growth are highly uncertain. In addition, Chapter 4 tested the equality of marginal returns and marginal costs of ICT capital. The results suggested that deviations from this equality may be informative about intangible investments. Hence both chapters illustrate that growth accounting assumptions are a useful starting point of the analysis. Furthermore, the deviations from the standard assumptions are neither certain nor stable enough to take them as the basis for further analysis. This leads to the conclusion that growth accounting provides a consistent framework for analysis, and serves as a useful point of departure for analyzing the sources of growth and differences in performance across economies.

6.4 An agenda for European reform

The main economic benefits from the introduction of the euro are likely to be a greater degree of competition and higher growth rates in the European Union. This is in line with the goal of the Lisbon agenda which aims to strengthen European competitiveness. The main policy question is what European countries should do to achieve these goals. The analysis in the first part of this study (Chapters 2 and 3) showed that the costs of the monetary union are probably not going to be excessive. However, the uncertainties about the future degree of coordination in fiscal policy and specialization across countries make the future degree of synchronization and hence the costs of the monetary union uncertain. One way of mitigating these costs is to make European labour markets more flexible. Specifically, it should be easier for workers to move across borders. However, the ease with which Americans move across the U.S. to chase better jobs and opportunities is likely to remain a distant goal for the foreseeable future. Europeans face not just language and cultural barriers, but pensions and insurance systems continue to differ substantially across countries. Improving the degree of flexibility should still be an important goal for the European Union though, as it is also likely to improve productivity growth.

Stimulating competitiveness is not straightforward, but the analysis in this study suggests a number of policy measures. Chapter 4 showed that the U.S. has been reaping more of the productive benefits of ICT than Europe. The U.S. has invested more in ICT and has been realizing many of the soft savings earlier than Continental European countries. One reason for this U.S. advantage is that it is easier not just to start new firms, but also for those new firms to grow quickly. There are many regulations in the areas of product markets that restrict restructuring and inhibit the start of new economic activities. Investments in intangibles (such as R&D, training, organizational innovations) are often costly and risky and will not be undertaken in an environment that is too restrictive. Hence the gains from intangible investments will be limited, which in turn reduces the potential gains from ICT investment. European countries should enact reforms to enable good firms, which are those which successfully invest in restructuring and start new activities, to excel and failing firms to exit. Lowering hiring and firing costs should help to do both. In addition, reducing differences in regulation across countries will further assist in reaping economies of scale through ICT investment projects that rely on a large scale. Given the strong advantage of market services in the U.S., the European Union should give priority to liberalizing services markets across countries.

During the 1990s, most European countries struggled to bring inflation and deficits under control. In the end, inflation and deficits converged to the lower levels, such as those historically experienced in Germany, and not to the high levels of Italy. To unlock the benefits of ICT and stimulate competitiveness, a similar convergence may be necessary in the area of regulation. This should stimulate productivity growth by enabling more experimentation with new business models, as well as allow for more cross-border activity. Greater flexibility of product and labour markets will not just make it easier to respond to cyclical shocks but also to technological opportunities.

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Chapter 4 is built on databases constructed over the past few years by many people at the Groningen Growth and Development Centre (GGDC) and (in parts) by the National Institute of Economic and Social Research (NIESR) in London. My main contribution has been constructing the initial version of the 60-industry database, as well as much of the industry investment data used for growth accounting. The software to analyze these databases is also by my hand. The growth accounts for the total economy as well as updating in recent years are mostly the work of Gerard Ypma and Edwin Stuivenwold (both GGDC).[169] The chapter itself is mostly based on joint work with Bart van Ark (van Ark and Inklaar, 2005). I contributed most of the empirical analysis and considerable parts of the drafting. Chapter 5 is fully my own work (see also Inklaar, 2005). However, just as for Chapter 4, the underlying data are based on the work of many at the GGDC.

[169] The key references for these databases are van Ark *et al.* (2002) for the total economy growth accounts, van Ark *et al.* (2003b) for the first version of the 60-industry database and Inklaar *et al.* (2005) for the industry growth accounts.

Samenvatting (summary in Dutch)

De Europese Unie kent momenteel twee belangrijke economische projecten die erop gericht zijn de concurrentiekracht van de Europese economieën te stimuleren. In de eerste plaats heeft een groot deel van de lidstaten sinds 1999 een gemeenschappelijke munt, de euro. In de tweede plaats hebben de regeringsleiders in 2000 de Lissabon agenda onderschreven die erop gericht is om Europa tot de meest concurrerende economie ter wereld te maken.[170] De doelstellingen van beide projecten zijn echter nog niet gehaald en de voortgang gaat niet zonder slag of stoot. Zo blijft de Europese arbeidsproductiviteitsgroei al 10 jaar achter bij de groei in de Verenigde Staten. De Europese Commissie (2004) spreekt dan ook over Europa's 'structurele productiviteitsprobleem.'

Grotere concurrentiekracht, en vooral hogere arbeidsproductiviteitsgroei, is van groot belang voor de versterking van Europa's economische prestaties. Op korte termijn kan de levenstandaard stijgen doordat een groter deel van de bevolking betaalde arbeid verricht of langer werkt, maar op lange termijn is een hogere productie per gewerkt uur essentieel. De vergrijzing in de rijke landen en de sterke opkomst van de economieën van China en India versterken de noodzaak van hogere productiviteitsgroei en innovatie. Vergrijzing zorgt ervoor dat in de komende jaren de beroepsbevolking afneemt en het aantal gepensioneerden toeneemt. Een hogere productiviteit kan eraan bijdragen dat pensioenen in de toekomst betaalbaar blijven.

Productie van een aantal goederen, zoals kleding en speelgoed, vindt steeds vaker plaats in lagelonenlanden (zoals in China) en ook bepaalde diensten, zoals het schrijven van computerprogramma's, blijken voor uitbesteding (bijvoorbeeld naar India) in aanmerking te komen. Een ander schrikbeeld in West-Europa is de komst van de goedkope loodgieter uit Polen. De reactie op deze globalisering is veelal een roep om

[170] Met Europa doel ik op de 15 landen die lid waren van de Europese Unie voor de toetreding van 10 nieuwe lidstaten op 1 mei 2004.

bescherming van de binnenlandse markt door middel van importquota's tot het aan banden leggen van het vrije verkeer van arbeid in de Europese Unie. Hoewel globalisering vooral aan de onderkant van de arbeidsmarkt voor problemen kan zorgen, is het vooral de snelle Amerikaanse productiviteitsgroei die een grotere uitdaging voor Europa vormt. De groeiachterstand ten opzichte van de VS suggereert dat Europa niet alleen een concurrentieprobleem heeft ten opzichte van lage-lonenlanden, maar dat het ook niet kan meekomen in termen van innovatie en gebruik van nieuwe technologieën.

De introductie van de euro brengt ook belangrijke uitdagingen met zich mee. Een belangrijk voordeel van de invoering van de euro is dat het economische integratie en groei kan bevorderen. Zowel op korte als op lange termijn zijn er echter ook uitdagingen. De Europese Centrale Bank (ECB) moet vorm geven aan een gezamenlijk monetair beleid voor een, in economisch opzicht, heterogeen gebied. Op korte termijn is dit een beperkt probleem omdat de ECB om zich op het eurogebied als geheel richt.

Op langere termijn kan de heterogeniteit echter een bedreiging vormen voor het voortbestaan van de euro. Met de invoering van de euro hebben de deelnemende landen hun monetair beleid uit handen gegeven en zijn daarmee een instrument kwijtgeraakt waarmee ze op economische ontwikkelingen kunnen reageren. Als de stand van de conjunctuur sterk verschilt tussen de verschillende landen, zal het gezamenlijke monetair beleid niet passend zijn voor elk van de lidstaten.

Hoofdstuk 2 gaat in op één van de praktische problemen waar de ECB mee te maken heeft. Bij het bepalen van het gezamenlijk monetair beleid is de stand van de euro-economie een van de bepalende factoren. Een probleem hierbij is echter dat cijfers met betrekking tot het BBP alleen op kwartaalbasis beschikbaar zijn en dat de BBP schattingen vaak met een flinke vertraging worden gepubliceerd. De ECB moet echter elke maand beslissen of het monetair beleid aanpassing behoeft. Een belangrijke vraag hierbij is hoe informatie uit de verschillende lidstaten gecombineerd kan worden om inzicht in de economie van het eurogebied als geheel te krijgen. Een instrument om hierbij te helpen is een conjunctuurindex. Deze index is doorgaans samengesteld uit reeksen die in ieder geval maandelijks beschikbaar zijn, zoals industriële productie, aandelenkoersen en detailhandelomzet. De vraag is hoe deze variabelen het beste in één index gecombineerd kunnen worden.

Er zijn ruwweg twee benaderingen om een conjunctuurindex samen te stellen. Volgens de eerste benadering selecteren analisten de reeksen, waarbij voor elke variabele wordt gekeken hoe goed ze de algehele conjunctuur volgen. De andere benadering gebruikt een statistisch model om het belang van elk van de variabelen in de index te bepalen. Vooral recentelijk zijn met behulp van statistische methoden conjunctuurindices geconstrueerd waarin informatie uit honderden variabelen wordt gecombineerd. Hoofdstuk 2 vergelijkt hoe goed beide benaderingen erin slagen om de conjuncturele ontwikkeling van het eurogebied te vangen. Het blijkt dat een index op basis van een beperkt aantal variabelen (minder dan 40) voor drie grote euro landen (Frankrijk, Duitsland en Spanje) al een goed beeld van conjunctuur in het eurogebied geeft. Een voordeel van dit beperkte aantal variabelen is dat gemakkelijker is te achterhalen welke factoren een belangrijke rol spelen in veranderingen van de index. Over de gehele periode bezien blijkt elk van de landen redelijk goed in de pas te lopen met de conjunctuur van het volledige eurogebied. Er zijn echter ook verschillen. Zo blijkt de industriële productie in Duitsland een veel grotere rol te spelen in de Europese conjunctuur dan dezelfde variabele in Frankrijk of Spanje. Dit suggereert dat het van belang is om nauwkeuriger te kijken naar de samenhang van de conjunctuur in het eurogebied.

Hoofdstuk 3 analyseert in hoeverre de conjunctuurbewegingen in de verschillende euro landen op elkaar lijken en probeert een inschatting te maken hoe de synchronisatie van de conjunctuurbewegingen zich in de monetaire unie zal ontwikkelen. Hoewel sinds de jaren ’70 de monetaire integratie in de Europese Unie steeds meer vorm heeft gekregen, heeft dit slechts geleid tot een geringe toename van de synchronisatie van de conjunctuur binnen het eurogebied. Bovendien fluctueert de mate van synchronisatie redelijk sterk door de tijd. Een analyse voor de Verenigde Staten laat zien dat dergelijke fluctuaties vermoedelijk ook in de toekomst belangrijk zullen blijven. Hoewel de Verenigde Staten al lang een monetaire unie vormen, zijn er perioden geweest waarin veel staten een conjunctuurbeweging hebben laten zien die sterk afwijkt van het landelijk beeld. Daarnaast zijn er ook perioden geweest, zoals bijvoorbeeld de Grote Depressie in de jaren ’30, waarin nationale ontwikkelingen domineerden en de mate van synchronisatie derhalve erg hoog was.

Om een nauwkeuriger beeld te krijgen van de toekomstige ontwikkeling van synchronisatie worden in Hoofdstuk 3 de determinanten van synchronisatie bestudeerd. Hieruit volgt dat een aantal variabelen robuust gerelateerd is aan synchronisatie. Zoals eerder onderzoek al heeft aangetoond, blijken landen met een grotere handelsintensiteit een meer synchroon lopende conjunctuurbeweging te vertonen dan landen die minder intensief met elkaar handelen. Het blijkt echter ook dat een grotere mate van overeenstemming in monetair beleid, financieel overheidsbeleid, correlatie van aandelenrendementen en minder wisselkoersvariabiliteit en minder specialisatie tot hogere synchronisatie leiden. Bovendien heeft elk van deze factoren een ongeveer even groot effect op synchronisatie als de handelsintensiteit.

De implicaties voor de toekomstige ontwikkeling van conjunctuursynchronisatie liggen voor de hand. Ten eerste, onder invloed van de gemeenschappelijke monetaire politiek zullen de economische ontwikkelingen in de landen in het eurogebied meer synchroon gaan lopen. De kans dat deze politiek mogelijk niet voor alle landen optimaal is, wordt minder groot. Ten tweede, indien alle landen een vergelijkbaar begrotingsbeleid voeren zal dat eveneens leiden tot meer synchronisatie. Vanuit het perspectief van de analyse in Hoofdstuk 3, zijn de tekortnormen in het Stabiliteits- en Groeipact als zodanig niet doorslaggevend voor de convergentie in conjuctuurcycli. Van belang is wel dat het begrotingsbeleid van de eurolanden niet te sterk verschilt. Een homogeen begrotingsbeleid zal een positieve bijdrage leveren aan het succes van het gemeenschappelijke monetaire beleid.

De ontwikkeling van specialisatiepatronen binnen de EU en het gevolg voor synchronisatie is lastiger te voorspellen. Onderzoek voor de VS laat zien dat door een grotere mobiliteit van productiefactoren, de productiestructuur van regio's in de VS homogener is geworden. Bovendien is sinds de jaren '70 de specialisatiegraad binnen Europa afgenomen.[171] Deze resultaten suggereren dat de conjunctuur binnen het eurogebied uniformer zal worden. Dit neemt niet weg dat er vermoedelijk altijd verschillen zullen blijven en dat een hogere mate van flexibiliteit, met name op de arbeidsmarkt, wenselijk is.

[171] Hierbij wordt vooral gekeken naar de goederensamenstelling van handelsstromen.

Wanneer is vastgesteld dat de kosten van de euro vermoedelijk beheersbaar zullen blijven, resteert de vraag hoe de Europese economieën hun concurrentiekracht kunnen versterken. Hoofdstukken 4 en 5 analyseren de productiviteitsgroei in Europa, waarbij Hoofdstuk 4 zich richt op de structurele factoren en Hoofdstuk 5 zich concentreert op het het belang van cyclische factoren in de productiviteitsgroei. Eén van de voornaamste redenen waarom de Europese arbeidsproductiviteitsgroei achterblijft bij de groei in de VS is de geringere bijdrage van informatie- en communicatietechnologie (ICT) aan groei. Allereerst is de ICT producerende sector in de VS groter dan in Europa, maar het belang van dit verschil is kwantitatief beperkt. Belangrijker is dat Amerika meer investeert in ICT en deze nieuwe technologie productiever gebruikt dan Europa.

Het effect van de hogere investeringen in ICT kan worden vastgesteld door middel van zogenaamde groeirekeningen. In groeirekeningen wordt verondersteld dat het aandeel in de totale kosten van kapitaalgoederen een goede indicator is voor de bijdrage aan de productie. Hiermee is een gedeelte van arbeidsproductiviteitsgroei toe te schrijven aan een bijdrage van een grotere hoeveelheid kapitaal per gewerkt uur. Het restant wordt totale factor productiviteitsgroei genoemd. Binnen dit raamwerk is het echter lastiger om het effect van ICT gebruik op de productiviteit vast te stellen. Een eerste aanwijzing voor een productiviteitsvoordeel in de VS is dat de dienstverlenende sector aldaar de grootste ICT investeerder is en dat juist deze sector een sterke groeispurt heeft laten zien sinds de tweede helft van de jaren '90.[172] Directer bewijs kan worden ontleend aan een econometrische analyse op bedrijfstakniveau. Volgens de traditionele neoklassieke groeitheorie, waarop de groeirekeningen zijn gebaseerd, moet de marginale productiviteit van ICT kapitaal gelijk zijn aan de marginale kosten. In de praktijk blijkt dit in de jaren '70 en jaren '90 inderdaad het geval te zijn. Gedurende de jaren '80 was de marginale productiviteit echter lager dan op basis van de kosten verwacht zou mogen worden. Dit U-patroon is in zowel Europa als de VS te zien, maar in de Angelsaksische landen (Verenigd Koninkrijk en Verenigde Staten) vond elke fase een aantal jaren eerder plaats dan in continentaal Europa (Frankrijk, Duitsland en Nederland).

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[172] Bovendien is deze groeispurt niet alleen aan hogere ICT investeringen te danken maar vooral aan een toename van de totale factorproductiviteit, wat kan betekenen dat innovaties in de sectoren zelf vruchten afwerpen.

Een verklaring voor het U-patroon is dat in de beginfase van ICT investeringen de productiviteitsverhogingen relatief makkelijk te realiseren waren, maar dat complementaire innovaties nodig zijn om aanvullende productiviteitswinsten te boeken. Dit kan worden geïllustreerd aan de hand van een voorbeeld voor de detailhandel. Zo zorgde de introductie van barcode scanners in supermarkten voor een aanzienlijke versnelling van het betalingsproces dat relatief eenvoudig zorgde voor productiviteitswinsten. Barcode scanners leveren echter ook veel informatie op over het koopgedrag van consumenten en deze informatie kan worden gebruikt om het bevoorraadingsproces te stroomlijnen. Hiervoor moet het organisatieproces van supermarkten echter aanzienlijk worden aangepast en moeten innovaties bijvoorbeeld ook worden gerealiseerd in aanpalende bedrijfstakken, zoals de transportsector.

Hoewel er weinig barrières zijn voor investeringen in ICT hardware en software, zijn complementaire innovaties veel moeilijker te realiseren. Dit suggereert dat de dynamiek binnen het bedrijfsleven moet worden gestimuleerd om meer van de productiviteitsvruchten van ICT te plukken. Rigide markten, met name in de sfeer van arbeids- en produktmarkten spelen hierbij een belangrijke rol. Strikte bestemmingsplannen maken het bijvoorbeeld lastig om snel winkels volgens een nieuw concept op te zetten en te openen.

Hoofdstuk 4 concludeert dat structurele factoren van belang zijn voor het verklaren van de achterblijvende arbeidsproductiviteitsgroei in Europa ten opzichte van de VS. Zeker op korte termijn kunnen cyclische factoren echter ook een rol spelen. Het blijkt namelijk dat productiviteitsgroei hoger is in perioden van snelle economische groei en relatief laag tijdens recessies. Dit kan betekenen dat productiviteitsschokken de conjunctuur bepalen of dat de (gemeten) productiviteit niet alleen beïnvloed wordt door aanbodfactoren maar ook door vraagfactoren. Hoofdstuk 5 onderzoekt een tweetal vraagfactoren waarmee eerder is geprobeerd cyclische productiviteit op geaggregeerd niveau te verklaren voor de VS.

Ten eerste wordt er gekeken of toenemende schaalopbrengsten van belang kunnen zijn voor procyclische productiviteit. In het geval van toenemende schaalopbrengsten neemt de productie meer dan proportioneel toe bij een toename in productiefactoren. In perioden van groei stijgt daardoor de productiviteit, terwijl productiviteit daalt ten tijden van recessies. Een tweede mogelijkheid is dat ongemeten inzet van productiefactoren van belang is. Aanpassingkosten voor kapitaal en arbeid zorgen ervoor dat bedrijven in de opgaande fase van de cyclus niet meer personeel aannemen of meer investeringen doen. In plaats daarvan wordt bijvoorbeeld de bestaande kapitaalgoederenvoorraad gedurende meer uren per week ingezet. Het niet adequaat meten van deze extra inzet leidt tot een onderschatting van het niveau van de productiefactoren in perioden van groei en een onderschatting in perioden van krimp. Hierdoor is (gemeten) productiviteit ook procyclisch.

Het blijkt dat deze verklaringen voor andere landen dan de VS minder (statistische) verklaringskracht hebben, maar dat ook in Europa de mate van cyclicaliteit van productiviteitsgroei afneemt. De analyse toont echter ook dat in veel individuele bedrijfstakken deze correlatie nog steeds significant positief is. Aangezien het economisch model met ongemeten inzet van productiefactoren is gebaseerd op een beschrijving van het gedrag van individuele bedrijven, is de verwachting dat de verklaringskracht op het meest gedetailleerde niveau minstens zo groot moet zijn als voor de gehele marktsector. Dit roept twijfels op over de validiteit van het economisch model. Een betere verklaring van cyclische productiviteit laat echter nog op zich wachten.

Tenslotte blijkt dat wanneer productiviteitsgroei wordt aangepast voor variabele schaalopbrengsten en ongemeten inzet van productiefactoren, het diverse groeipatroon tussen de VS en Europa niet wezenlijk verandert. Zo is de aangepaste productiviteitsgroei in de VS nog steeds hoger dan in Europa, mede dankzij snelle groei in de dienstverlenende sector. Bovendien is de omvang en zelfs het teken van de aanpassing erg onzeker.

Samenvattend, structurele factoren lijken een dominante te spelen in het verklaren van de achterlopende arbeidsproductiviteitsgroei in Europa. Zoals Hoofdstuk 4 beargumenteert, remt regulering de productieve toepassing van ICT en moet het voor goede bedrijven makkelijker worden gemaakt om snel te kunnen groeien terwijl slechte bedrijven sneller failliet moeten kunnen gaan. Ook deregulering van de arbeidsmarkt, en vooral lagere ontslagkosten, kunnen de dynamiek van de Europese bedrijvigheid vergroten. Daarnaast helpen deze maatregelen ook om Europese economieën weerbaarder te maken tegen een conjunctuur die uit de pas loopt bij de rest van Europa.